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ML 6143 Prof Sundeep Ragan

PRJOECT: NITS CBRS RADAR 3.5 GHz Waveform Detection

RadarWaveformsML - Detecting the Presence of the Waveform Immersed in Gaussian Noise using PCA

Manipulation of Radar and Communication Waveforms using new ML algorithms but not forgetting the Old Tricks

This repository was originally created for project for the Class "Introduction to Machine Learning at NYU Tandon" ministered by Professor Sundeep Ragan (more details at https://github.com/sdrangan/introml (https://github.com/sdrangan/introml))

The main goal is to use synthetic radar waveforms (**RF Dataset of Incumbent Radar Systems in the 3.5 GHz CBRS Band**) provided by the scientists at the US National Institute of Standards and Technology (NIST) (more details at https://data.nist.gov/od/id/mds2-2116 (https://data.nist.gov/od/id/mds2-2116)) to investigate the detection of features in the waveforms using *Machine Learning* techniques.

We are interested in simple trainable algorithms that able to detect the waveforms in the presence of noise (and also fading in the future). We are also interested in find the *signatures* of the waveforms to be able to classify the different radar waveforms and differentiate them from other electromagnetic signals, like the ones used for microwave wireless communications.

Real-time time identification of waveforms is an important tool that can be used to allow coexistence of different emitters sharing the same geographical space. It is also relevant for cyber-security, helping to assure security in cyber-physical environments.

NOTE: to develop the code here we used examples provided in the NIST directory about how read the data files and label files fields correctly in the Python Programming Language. The MATLAB code used by the scientists at NIST to generated radar wavforms simililar to the ones they made avaiable can be found at

https://github.com/usnistgov/SimulatedRadarWaveformGenerator.git/trunk (https://github.com/usnistgov/SimulatedRadarWaveformGenerator.git/trunk)

NIST Data Website https://data.nist.gov/od/id/mds2-2116 (https://data.nist.gov/od/id/mds2-2116)

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Importing some Libraries

In [1]:
```
import numpy as np
import h5py
from   pathlib import Path
import pandas as pd
import matplotlib.pyplot as plt
GDRIVE_MOUNTED=False
```

Some Details about How to Dowload RF Dataset of Incumbent Radar Systems in the 3.5 GHz CBRS Band

Each file has 200 synthetically created waveforms, each being 80 ms long. Some waveorms have only gaussian noise. Others have radar waveforms immersered in gaussian noise under several different SNR. Radar waveforms can be different types of simple pulse trains or more complex chirped waveforms.

Each file size is 2.5 GB. The total dataset is 500 GB! We will use just a few files from the database. Additional small csv files provide different types of labels related to the data.

The data can be download directly from NIST using the link https://data.nist.gov/od/id/mds2-2116 (https://data.nist.gov/od/id/mds2-2116)

For convencience, a subset of of the data was downloaded in the Google drive and is accessible for people from NYU. The shared link below provides access to the NYU folks. The shared folder has the same structure as the NIST database but only few of the large waveform files.

https://drive.google.com/drive/folders/1IhVG7mAMoTFjsXbArvrz3cEIXDIJVnDS?usp=sharing (https://drive.google.com/drive/folders/1IhVG7mAMoTFjsXbArvrz3cEIXDIJVnDS?usp=sharing)

Once the code is copied into the person google drive, the code below can be easily adjusted to access the data by chaning the variables *data_folder* and *remote_folder_gdrive*. The code below also allows to run the iphython notebook locally in the machine. In this case the variable *remote_folder_local* needs to be udpated

The code below also checks if GPU is enabled.

In [2]:
```
str_GPU='GPU'
#str_GPU='CPU' #To fake having a GPU
data_folder="SimulatedRadarWaveforms"
remote_folder_gdrive="./gdrive/My Drive/_BIG1/NIST/CBRS/"+data_folder
remote_folder_local="/G/_BIG1/NIST/CBRS/"+data_folder

import os
#!df -k | egrep "Filesystem|overlay"
#!ls

# MOUNT GDRIVE
if 'google.colab' in str(get_ipython()):
  GCOLAB_ENV=True
  print('***RUNNING on CoLab')
  if False==GDRIVE_MOUNTED:
    from google.colab import drive
    drive.mount("/content/gdrive")
    GDRIVE_MOUNTED=True
else:
  print('***NOT RUNNING on CoLab')
  GCOLAB_ENV=False

# CHECK if System has GPU
from tensorflow.python.client import device_lib
resp = device_lib.list_local_devices()
if str_GPU in str(resp):
  has_gpu=True
  gpu_info = !nvidia-smi
  gpu_info = '\n'.join(gpu_info)
  if gpu_info.find('failed') >= 0: print('GPU Info NOT AVAILABLE (!?!)')
  else:                            print(gpu_info)
else:
  has_gpu=False

# LOAD Data
if True==GCOLAB_ENV:
  data_folder_full = remote_folder_gdrive
  #!rsync -av "$remote_folder"   .
  #!du        "$data_folder"
  #!rsync -av "$data_folder"     .
else:
  data_folder_full = remote_folder_local

print('Data Folder:', data_folder_full)
!ls -l     "$data_folder_full"

!rm -rf ./flickr2
if (True==has_gpu):
  print("*** DO SOMETHING (HAS GPU)")
else:
  print("*** DO SOMETHING (HAS NO GPU)")
```

```
***NOT RUNNING on CoLab
Data Folder: /G/_BIG1/NIST/CBRS/SimulatedRadarWaveforms
total 3789
-rwxrwxrwx 1 root root 3864830 Nov 19 08:05 allWaveformsTableCombined.csv
-rwxrwxrwx 1 root root      64 Nov 19 08:05 allWaveformsTableCombined.csv.sha
256
-rwxrwxrwx 1 root root     136 Dec  9 21:40 desktop.ini
dr-xr-xr-x 1 root root    4096 Dec  9 21:40 Group1
dr-xr-xr-x 1 root root       0 Dec  9 21:40 Group2
dr-xr-xr-x 1 root root       0 Dec  9 21:40 Group3
dr-xr-xr-x 1 root root       0 Dec  9 21:40 Group4
-rwxrwxrwx 1 root root    2282 Nov 19 08:04 License.txt
-rwxrwxrwx 1 root root      64 Nov 19 08:04 License.txt.sha256
-rwxrwxrwx 1 root root    1399 Nov 19 08:05 ReadMe.txt
-rwxrwxrwx 1 root root      64 Nov 19 08:04 ReadMe.txt.sha256
dr-xr-xr-x 1 root root    4096 Dec  9 21:40 readWaveformsCodeExamples
*** DO SOMETHING (HAS NO GPU)
```

Reading the Radar Waveform Data Set .mat files and the .csv file with the Additional Labels

This will take some time because the files are large.

In [3]:
```
#dataRootFolder=data_folder
group_No =1  # 1 to 4
subset_No=2 # 1 to 50
# Preps
dataRootFolder  =data_folder_full
fileName        ='group'+str(group_No)+'_subset_'+str(subset_No)+'.mat'
filePath        =Path(dataRootFolder)/('Group'+str(group_No))/(fileName)
waveform_var    ='group'+str(group_No)+'_waveformSubset_'+str(subset_No)
status_var      ='group'+str(group_No)+'_radarStatusSubset_'+str(subset_No)
table_var       ='group'+str(group_No)+'_waveformTableSubset_'+str(subset_No)
infoFileNamePath=Path(dataRootFolder)/('Group'+str(group_No))/('group'+
                     str(group_No)+'_subset_CSVInfo')/(table_var+'.csv')
#
# Read data from .mat file
h5pyObj           = h5py.File(filePath,'r')
subsetSignals     = h5pyObj[waveform_var][()].view(np.complex)
subsetRadarStatus = h5pyObj[status_var  ][()]
#
# Now use Panda to read the info csv file
subsetInfo = pd.read_csv(infoFileNamePath)

print('***DONE')
```

```
***DONE
```

Now Printing Some Fields to Get Familiar with the Data

Two label columns of spectial interest are *subsetRadarStatus=h5pyObj[status_var]* and *

1. h5pyObj[status_varList]: Indicates if a radar waveform is present
2. subsetInfo['BinNo']: Indicates the type of the waveform
3. subsetInfo['SNR']: Indicates the Signal-to-Noise Ratio when the radar waveform is present.

In [4]:
```
def P2R(radii, angles):
    return radii * np.exp(1j*angles)

def R2P(x):
    return np.abs(x), np.angle(x)
```

In [5]:
```
jj = 1.j
print("fileName    =", fileName)
print("waveform_var=", waveform_var)
print("status_var  =", status_var)
print("table_var   =", table_var)
print("h5pyObj     =", h5pyObj)
print('---')
print('[',waveform_var,'   ] subsetSignals.shape=',subsetSignals.shape)
print('[',status_var  ,'] subsetRadarStatus.shape=',subsetRadarStatus.shape)
print('subsetInfo.shape=' ,subsetInfo.shape)
print('---')
print('[',waveform_var,'   ] subsetSignals.shape=',subsetSignals.shape)
NPT=5
r, ang = R2P(subsetSignals[0, 0:NPT])
#print(subsetSignals[sigIndex, 0:NPT])
#print('r=\n', r.T)
#print('ang=\n', ang.T)
print(r*np.exp(jj*ang))
```

```
fileName    = group1_subset_2.mat
waveform_var= group1_waveformSubset_2
status_var  = group1_radarStatusSubset_2
table_var   = group1_waveformTableSubset_2
h5pyObj     = <HDF5 file "group1_subset_2.mat" (mode r)>
---
[ group1_waveformSubset_2    ] subsetSignals.shape= (200, 800000)
[ group1_radarStatusSubset_2 ] subsetRadarStatus.shape= (200, 1)
subsetInfo.shape= (200, 16)
---
[ group1_waveformSubset_2    ] subsetSignals.shape= (200, 800000)
[1.66089269e-07-2.31654912e-07j 1.35645134e-07+2.35493766e-07j
 1.58416011e-07-1.24614912e-07j 1.21105281e-07+4.92919982e-08j
 4.46692447e-07-3.11198016e-07j]
```

In [6]:
```
#%% show the info and status of the first 10
#print(subsetRadarStatus[0:20])
print("LABEL RADAR Waveform Present:\n\n", subsetRadarStatus[0:20].ravel())
print("\nOTHER LABELS below:\n")
print("...LABEL NAMES (Columns):\n... ...", subsetInfo.columns)
print("\n... ... LABELS:\n",subsetInfo[0:20])
aux=subsetInfo['SNR'];  print("SNRs Values in the file:", aux.unique());
aux=subsetInfo['BinNo'];print("WAVEFORMS   in the file:", aux.unique());
print('***DONE QUICKLY')
```

```
LABEL RADAR Waveform Present:

 [0 0 1 1 0 0 0 0 0 0 0 0 1 0 1 1 0 1 0 0]

OTHER LABELS below:

...LABEL NAMES (Columns):
... ... Index(['BinNo', 'PulseWidth', 'PulsesPerSecond', 'PulsesPerBurst',
       'ChirpWidth', 'ChirpDirection', 'SamplingFrequency', 'ActualPulseWidt
h',
       'PhaseCodingType', 'SUID', 'radarStatus', 'radarSignalCenterFreq',
       'radarSignalStartTime', 'SNR', 'NoisePowerdBmPerMHz', 'duration'],
      dtype='object')

... ... LABELS:
     BinNo  PulseWidth  PulsesPerSecond  PulsesPerBurst  ChirpWidth  \
0      NaN         NaN              NaN             NaN         NaN
1      NaN         NaN              NaN             NaN         NaN
2   Q3N#3    0.000085            800.0            20.0  50000000.0
3   P0N#2    0.000026           1690.0            10.0         NaN
4      NaN         NaN              NaN             NaN         NaN
5      NaN         NaN              NaN             NaN         NaN
6      NaN         NaN              NaN             NaN         NaN
7      NaN         NaN              NaN             NaN         NaN
8      NaN         NaN              NaN             NaN         NaN
9      NaN         NaN              NaN             NaN         NaN
10     NaN         NaN              NaN             NaN         NaN
11     NaN         NaN              NaN             NaN         NaN
12  Q3N#1    0.000003           1620.0            20.0  50000000.0
13     NaN         NaN              NaN             NaN         NaN
14  Q3N#1    0.000004            870.0            22.0  70000000.0
15  P0N#1    0.000002           1010.0            35.0         NaN
16     NaN         NaN              NaN             NaN         NaN
17  Q3N#2    0.000021           1750.0             2.0   3000000.0
18     NaN         NaN              NaN             NaN         NaN
19     NaN         NaN              NaN             NaN         NaN

   ChirpDirection  SamplingFrequency  ActualPulseWidth PhaseCodingType  \
0             NaN           10000000               NaN             NaN
1             NaN           10000000               NaN             NaN
2            Down           10000000          0.000085             NaN
3             NaN           10000000          0.000026          Barker
4             NaN           10000000               NaN             NaN
5             NaN           10000000               NaN             NaN
6             NaN           10000000               NaN             NaN
7             NaN           10000000               NaN             NaN
8             NaN           10000000               NaN             NaN
9             NaN           10000000               NaN             NaN
10            NaN           10000000               NaN             NaN
11            NaN           10000000               NaN             NaN
12           Down           10000000          0.000003             NaN
13            NaN           10000000               NaN             NaN
14             Up           10000000          0.000004             NaN
15            NaN           10000000          0.000002             NaN
16            NaN           10000000               NaN             NaN
17           Down           10000000          0.000021             NaN
18            NaN           10000000               NaN             NaN
```

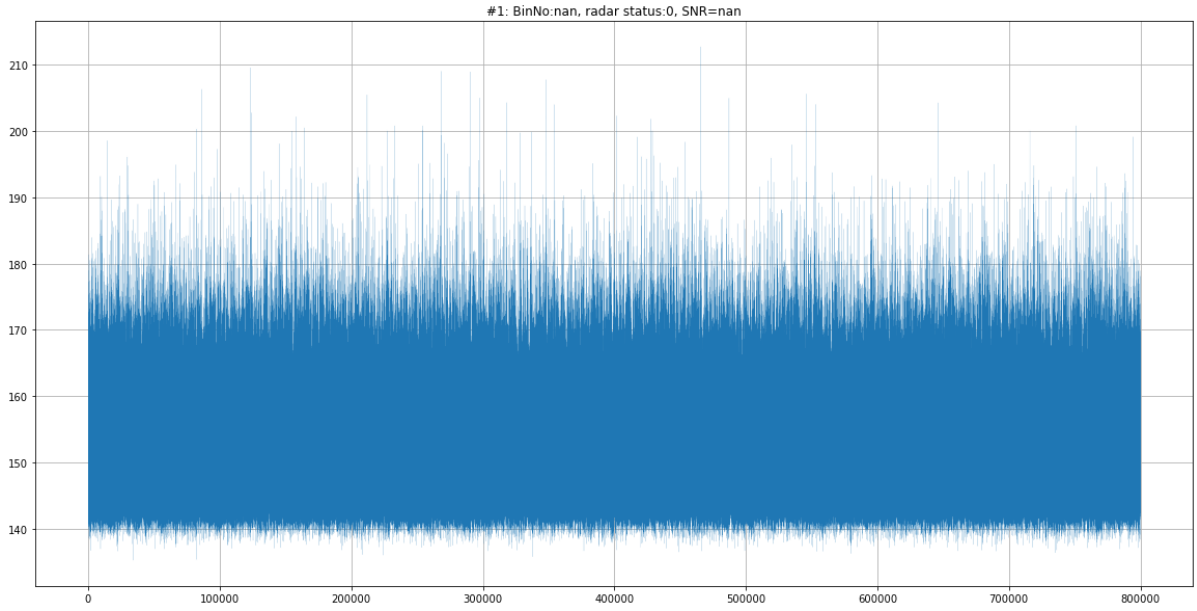
```
19           NaN           10000000              NaN             NaN

                                    SUID  radarStatus  radarSignalCenterFreq
\
0                                    NaN            0                    NaN
1                                    NaN            0                    NaN
2   1c19ef39-f88b-4ff9-a77d-68bc9eb141ef            1                    0.0
3   b6e3b197-b0ff-49d2-916c-5bc60df615e4            1              1623597.0
4                                    NaN            0                    NaN
5                                    NaN            0                    NaN
6                                    NaN            0                    NaN
7                                    NaN            0                    NaN
8                                    NaN            0                    NaN
9                                    NaN            0                    NaN
10                                   NaN            0                    NaN
11                                   NaN            0                    NaN
12  6ac0e889-f818-49de-9e7b-40779815a572            1                    0.0
13                                   NaN            0                    NaN
14  6d0b9cf4-8efd-4e2c-bc77-139f0c4a8054            1                    0.0
15  00c8c6d2-064b-4396-b340-b0ce8d321716            1               -705689.0
16                                   NaN            0                    NaN
17  f9643519-bda0-47e9-9ea0-9745406539c6            1              -1046091.0
18                                   NaN            0                    NaN
19                                   NaN            0                    NaN

    radarSignalStartTime   SNR  NoisePowerdBmPerMHz  duration
0                    NaN   NaN                 -109      0.08
1                    NaN   NaN                 -109      0.08
2               0.008170  10.0                 -109      0.08
3               0.015718  18.0                 -109      0.08
4                    NaN   NaN                 -109      0.08
5                    NaN   NaN                 -109      0.08
6                    NaN   NaN                 -109      0.08
7                    NaN   NaN                 -109      0.08
8                    NaN   NaN                 -109      0.08
9                    NaN   NaN                 -109      0.08
10                   NaN   NaN                 -109      0.08
11                   NaN   NaN                 -109      0.08
12              0.018937  16.0                 -109      0.08
13                   NaN   NaN                 -109      0.08
14              0.020553  14.0                 -109      0.08
15              0.022690  16.0                 -109      0.08
16                   NaN   NaN                 -109      0.08
17              0.022535  16.0                 -109      0.08
18                   NaN   NaN                 -109      0.08
19                   NaN   NaN                 -109      0.08
SNRs Values in the file: [nan 10. 18. 16. 14. 12. 20.]
WAVEFORMS   in the file: [nan 'Q3N#3' 'P0N#2' 'Q3N#1' 'P0N#1' 'Q3N#2']
***DONE QUICKLY
```

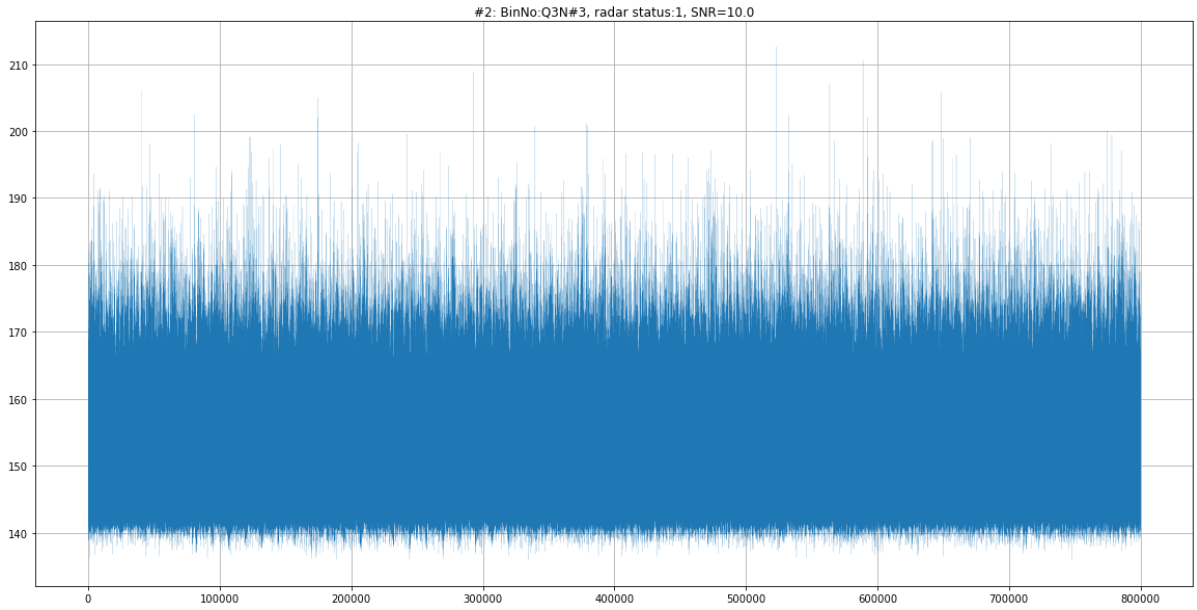
Below we plot three waveforms in the time domain.

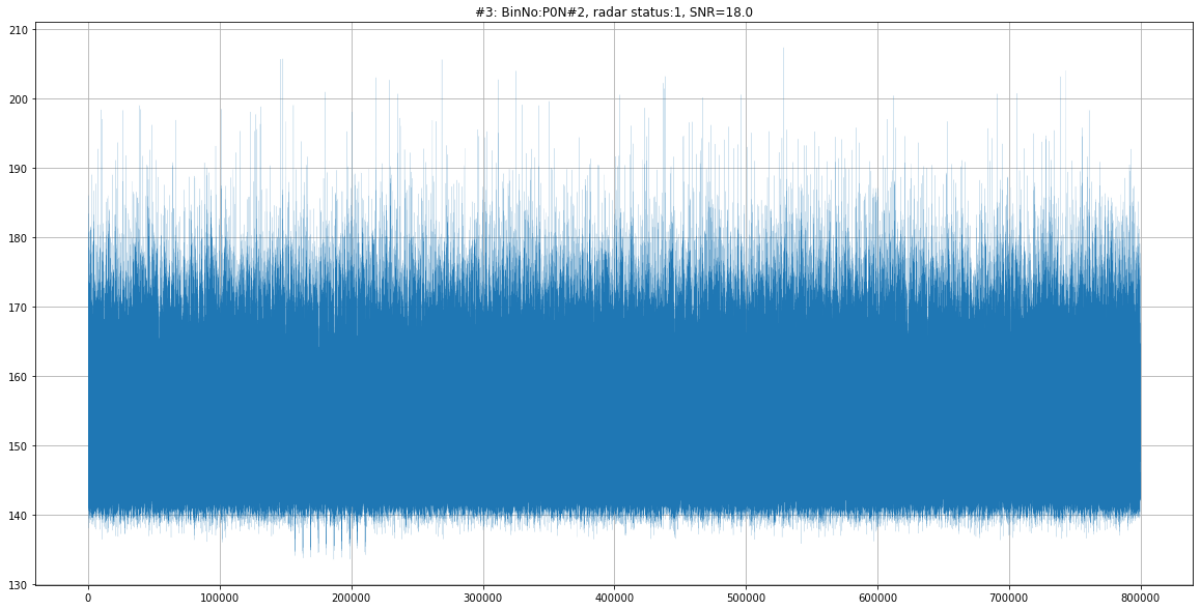
The first has only noise, the second has a relatively low SNR and the thrid a relatively higher SNR. Note that the signal can not be visually detected and it seems that only noise is present.

In [7]:
```
noExamples=3
startFrom=1
for sigIndex in range(startFrom,startFrom+noExamples):
      #sigIndex=6 # Matlab index 6
      print('***Doing for sigIndex=', sigIndex)
      plt.figure(figsize=(20,10))
      plt.plot(-10*np.log(np.absolute(subsetSignals[sigIndex][0:-1])),linewidt
h=0.1)
      plt.title('#'+str(sigIndex)+': BinNo:'+str(subsetInfo['BinNo'][sigIndex
])+', radar status:'+str(subsetInfo['radarStatus'][sigIndex])+', SNR='+str(sub
setInfo['SNR'][sigIndex]))
      plt.grid()
print('***DONE!')
```

```
***Doing for sigIndex= 1
***Doing for sigIndex= 2
***Doing for sigIndex= 3
***DONE!
```





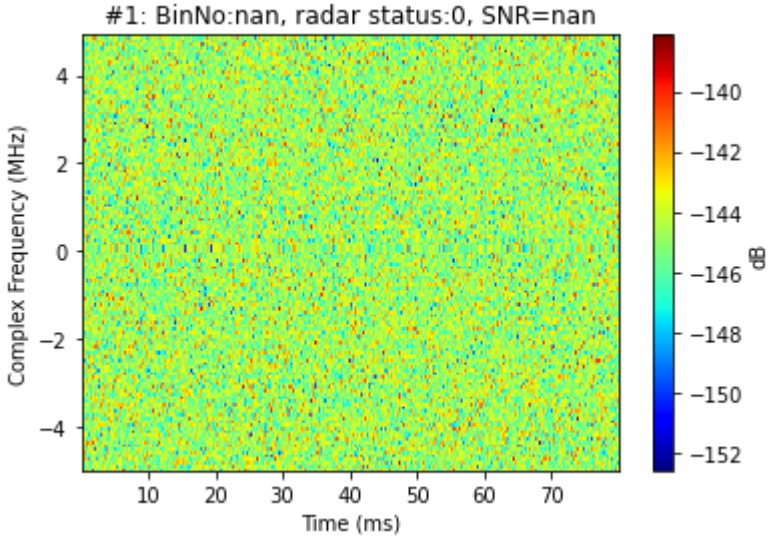


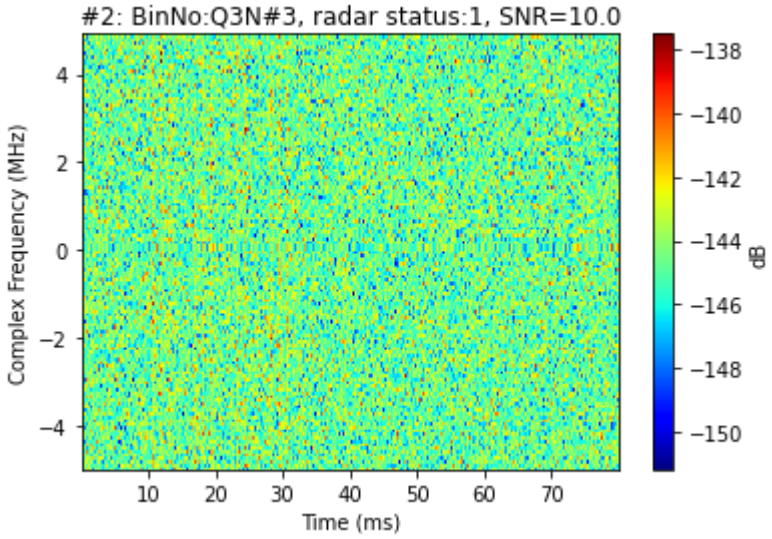
Below we Plot Three Waveforms in the Frequency vs Time Domain.

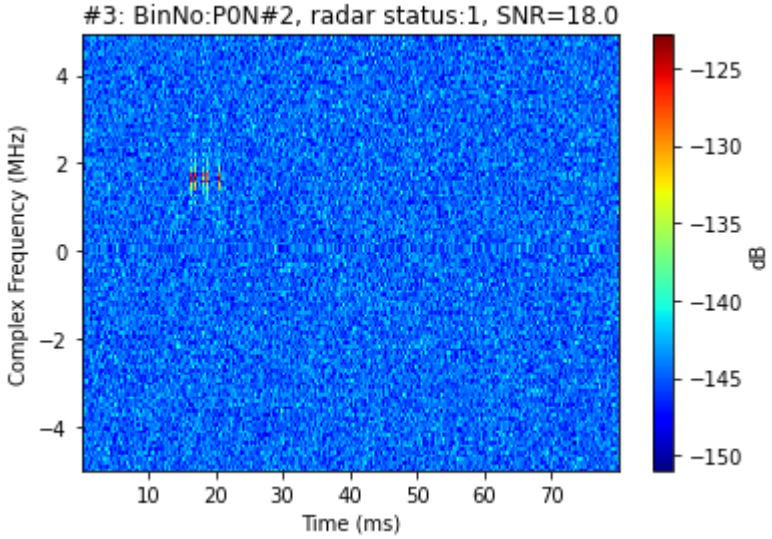
Again the first has only noise, the second has a relatively low SNR and the thrid a relatively higher SNR. Note that now the signal is resolved cells of time and frequency the signal can be seen as non-random cell patterns on top of the 'sea of noise'. It is hardly noticiable in the second case (SNR=10 dB), but still it can be seen lile a 'cat scratch' o lower left quadrant of the spectogram. In the case of the third spectorgram, the signal is much easier to see because of the higer SNR and also because the specific waveform used is short and 'shines more' above the noise 'sea level'

In [8]:
```
from scipy import signal
Nfft=128
groupby=16  # no. of consectuive FFTs over which to take max

noExamples=3
startFrom=1
for sigIndex in range(startFrom,startFrom+noExamples):
  f, t0, S0 = signal.spectrogram(subsetSignals[sigIndex], fs=10e6, nperseg=Nff
t, scaling='spectrum', return_onesided=False)
  print('S0.shape=', S0.shape)
  #
  S0[0:1, :] = S0[1:2, :]
  L = S0.shape[1]/groupby
  S1 = np.reshape(S0[:,:int(L)*groupby], (Nfft,int(L),groupby))
  S = np.amax(S1, axis=-1)
  t = t0[groupby-1::groupby]

  print('S.shape=', S.shape)
  #S[0:1, :] = np.mean(S[70:80,:], axis=0)
  #S[0:1, :] = S[1:2, :]
  fshi = np.fft.fftshift(f/1e6)
  Sshi = np.fft.fftshift(10.*np.log10(S), axes=0)
  #print('Sshi.shape=', Sshi.shape
  #
  #fig = plt.figure(figsize=(10,10))
  fig = plt.figure()
  cax = plt.pcolormesh(t*1e3, fshi, Sshi, cmap='jet')
  plt.title('#'+str(sigIndex)+': BinNo:'+str(subsetInfo['BinNo'][sigIndex])+',
radar status:'+str(subsetInfo['radarStatus'][sigIndex])+', SNR='+str(subsetInf
o['SNR'][sigIndex]))
  plt.xlabel('Time (ms)')
  plt.ylabel('Complex Frequency (MHz)')
  fig.colorbar(cax).set_label('dB')

print('***DONE!')
```

```
S0.shape= (128, 7142)
S.shape= (128, 446)
S0.shape= (128, 7142)
S.shape= (128, 446)
S0.shape= (128, 7142)
S.shape= (128, 446)
***DONE!
```






#3: BinNo:P0N#2, radar status:1, SNR=18.0
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−125
−130
−135
−140
−145
−150
dB

Below we Assess if PCA can Help with the Detection and Classification of Radar Waveforms

As the plots will confirm below, we are hunting for 'anomalies/disturbances' in the non-normalized PC decay curves with the hope that these changes (when compared to the channel with only gaussian noise) will provide some hints that will allow us to detect the presence of the signal and perhaps classify it based on this signature. As we will be able to see below, there are a small number of PCs from the second and on that can potentially give information about the presence waveforms. So some level of classitication based on PCs seem to be possible.

In Signal Intelligence, Cybersecurity or Waverform Co-existence Monitoring problems we don't know *a priori* the types of wavform that are present and their exact locations in time and/or frequency. This makes challenging to use **matched filters** techniques without **learning from the waveform data** the information about the signal we are tyring to filter match to maximize detection under noise.

One idea (naive perhaps we must add, because we haven't really checked papers and books about it or how to make it more efficient yet, because we are just trying to to explore ML techniques for signals) is to create a time frequency matrix (image) of the signal and used it as an input for ML algorithms. The time frequency analysis provides information about the signal and both domains and this is certainly important information to proper classify a waveform.

In the NIST data base the waveforms can one of six types [nan 'Q3N#3' 'P0N#2' 'Q3N#1' 'P0N#1' 'Q3N#2'], where 'nan' means that no waveform is present and additivive gaussian white noise comprises the recorded waveform time series. More information about the waveforms can be found in the NIST documentation referenced above.

Below we do a spectogram of the signal and do a **maxpool** of the data in the time domain in the way suggested by the example program provided by NIST to 'reduce' the signal in the tiem domain to fewer bins.

After that we do an **SVD** of the result matrix to discover the directions of maximum variation of the signal in the time domain space. As we see below, the first PC (singular value) is the one by two orders of magnitude larger, containing the majority of time/frequency variation. It is in this direction that most of noise and and signal variation concentrates in the time frequency space.

More Interestingly, the relative amplitudes of the PCs also change in the presence of a coherent, structured signal and the variations *leaks* in the rest of the PCs in different ways depending on the signal signature.

The stem plots below demonstrate that. So we raise the **hypothesis** that the PCAs relative distribution can be used to detect the presence of the signal and perhaps even tell what type of waveform is present, which is important to identify the emmmiter in some use cases.

Also, the images show interesting features of the waveforms. **The images themselves could be used for classification***. The better the time frequency extraction the easier is to extract indentifiable features for classfiication.

For the current exercise, ***we will focus in using the PCAs for classification with Logistic Regression***, but an obvious extension of this work would to use the images (the time frequency spectrogram matrices) do classification using SVM or Deep Neural Networks (*perhaps using transfer training, which is an intriguing and iteresting idea to explore per se*).

NOTE: in this problem we don't scale the data, this is because all the dimensions are alrady in same units and the realtive vaules of one against the other provide information about the classification. In our case we don't want a fidel reconstrution of signal. We aim for one the stresses the some of waveform characterists that help waveform classfication in the presence of the noise (a filter problem, but it does noeed to a be a 'perfect' filter in the sense to reconstruct the best representation of signal in the presence of noise - we want a reconstruction that optimizes classification and our hope/educated guess is that pca will help with that).

We will use the scaling provided by the signal.spectrogram() function.

In [9]:
```
from scipy import signal
plt.rcParams.update({'figure.max_open_warning': 0})
flag_make_it_150x150=True
pca0 = 1
nruns_noise  = 2
nruns_signal = 18
Nfft=128
groupby=16  # no. of consectuive FFTs over which to take max
nruns=nruns_noise + nruns_signal
if flag_make_it_150x150:
  Nfft=150
  groupby=40  # no. of consectuive FFTs over which to take max

# [10. 12. 14. 16. 18. 20.]
#IselWaves_signal=np.where(subsetInfo.SNR==10)
#IselWaves_signal=np.where(subsetInfo.SNR==14)
#IselWaves_signal=np.where(subsetInfo.SNR==16)
#IselWaves_signal=np.where(subsetInfo.SNR==18)
IselWaves_signal=np.where(subsetInfo.SNR==20)
IselWaves_noise=np.where(np.isnan(subsetInfo.SNR)) #Noise Only
IselWaves = []
rfix = Nfft//2
idx=1
for I in np.nditer(IselWaves_noise):
  if idx > nruns_noise: break
  IselWaves.append(int(I))
  idx += 1
idx=1
for I in np.nditer(IselWaves_signal):
  if idx > nruns_signal: break
  IselWaves.append(int(I))
  idx += 1

idx=1
for I in IselWaves:
  if idx > nruns: break
  #sigIndex=int(I)
  sigIndex=(I)
  if np.isnan(subsetInfo['SNR'][sigIndex]):
    stem_col = 'silver'
    wavstr = '\n(Gaussian Noise Only)'
  else:
    stem_col = 'coral'
    wavstr = '\n(Gaussian Noise + Signal)'

  print('***--------------------')
  print('***Doing for sigIndex=', sigIndex, 'I=', I)
  #print('...NSD   :', subsetInfo['NoisePowerdBmPerMHz'][sigIndex])
  print('...SNR   :', subsetInfo['SNR'][sigIndex])
  print('...BinNo :', subsetInfo['BinNo'][sigIndex])

  #
  f, t0, S0 = signal.spectrogram(subsetSignals[sigIndex], fs=10e6, nperseg=Nff
t, scaling='spectrum', return_onesided=False)
  #
  S0[0:1, :] = S0[1:2, :]
```

```
  L = S0.shape[1]/groupby
  S1 = np.reshape(S0[:,:int(L)*groupby], (Nfft,int(L),groupby))
  S = np.amax(S1, axis=-1)
  if flag_make_it_150x150: S=S[:,0:S.shape[0]] #Make is 150x150 Square
  t = t0[groupby-1::groupby]

  print('...S.shape=', S.shape)
  fshi = np.fft.fftshift(f/1e6)
  Sshi = np.fft.fftshift(10.*np.log10(S), axes=0)

  #from sklearn.preprocessing import StandardScaler
  #scal = StandardScaler()
  #scal.fit_transform(S)
  #Sc=scal.transform(S)
  #Sshi = np.fft.fftshift(Sc, axes=0)
  #print('...Sc.shape=', Sc.shape)

  u, s, vh = np.linalg.svd(Sshi, full_matrices=False);
  print('...U.shape=', u.shape)
  print('...S.shape=', s.shape)
  print('...Vh.shape', vh.shape)
  #
  aux = u.dot(np.diag(s)).dot(vh)
  print('...CHECKDIFFMAT (ORIG vs U.diag(S).Vh): ', np.max(np.abs(aux - Sshi
)))
  fig = plt.figure()
  cax = plt.pcolormesh(t*1e3, fshi, Sshi, cmap='jet')
  plt.title('Run# '+str(idx)+' '+str(subsetInfo['BinNo'][sigIndex])+' SPECTROG
RAM(All PCs)'+wavstr)
  plt.xlabel('Time (ms)')
  plt.ylabel('Complex Frequency (MHz)')
  fig.colorbar(cax).set_label('dB')
  #
  fig = plt.figure()
  scp = np.copy(s)
  scp[0:0+1] = 0; #Knocks 2nd PC
  aux = u.dot(np.diag(scp)).dot(vh)
  aux[rfix:rfix+2,:]=aux[rfix-2:rfix,:] #Workaround. Orig data has issues @0Hz
(?!). Not big prob 4us
  cax = plt.pcolormesh(t*1e3, fshi, aux, cmap='jet')
  plt.title('Run# '+str(idx)+' '+str(subsetInfo['BinNo'][sigIndex])+' SPECTROG
RAM (No PC1)'+wavstr)
  plt.xlabel('Time (ms)')
  plt.ylabel('Complex Frequency (MHz)')
  fig.colorbar(cax).set_label('dB')
  #
  fig = plt.figure()
  scp[1:1+1] = 0; #Knocks Off 1st PC Also
  aux = u.dot(np.diag(scp)).dot(vh)
  aux[rfix:rfix+2,:]=aux[rfix-2:rfix,:] #Workaround. Orig data has issues @0Hz
(?!). Not big prob 4us
  cax = plt.pcolormesh(t*1e3, fshi, aux, cmap='jet')
  plt.title('Run# '+str(idx)+' '+str(subsetInfo['BinNo'][sigIndex])+' SPECTROG
RAM (No PCs[1,2]])'+wavstr)
  plt.xlabel('Time (ms)')
  plt.ylabel('Complex Frequency (MHz)')
  fig.colorbar(cax).set_label('dB')
```

```
  #
  fig = plt.figure()
  scp = np.copy(s)
  scp[0:0+1] = 0; scp[8:] = 0; #Also 1st and all PCs after 8th
  aux = u.dot(np.diag(scp)).dot(vh)
  aux[rfix:rfix+2,:]=aux[rfix-2:rfix,:] #Workaround. Orig data has issues @0Hz
(?!). Not big prob 4us
  cax = plt.pcolormesh(t*1e3, fshi, aux, cmap='jet')
  plt.title('Run# '+str(idx)+' '+str(subsetInfo['BinNo'][sigIndex])+' SPECTROG
RAM (Only Pcs[2 to 8])'+wavstr)
  plt.xlabel('Time (ms)')
  plt.ylabel('Complex Frequency (MHz)')
  fig.colorbar(cax).set_label('dB')
  #
  fig = plt.figure()
  scp = np.copy(s)
  scp[0:0+1] = 0; scp[3:] = 0; #Now only 2nd and 3rd PC
  aux = u.dot(np.diag(scp)).dot(vh)
  aux[rfix:rfix+2,:]=aux[rfix-2:rfix,:] #Workaround. Orig data has issues @0Hz
(?!). Not big prob 4us
  cax = plt.pcolormesh(t*1e3, fshi, aux, cmap='jet')
  plt.title('Run# '+str(idx)+' '+str(subsetInfo['BinNo'][sigIndex])+' SPECTROG
RAM (Only Pcs[2,3])'+wavstr)
  plt.xlabel('Time (ms)')
  plt.ylabel('Complex Frequency (MHz)')
  fig.colorbar(cax).set_label('dB')
  #
  #aux = 100*np.sort(s)[::-1]/np.sum(s)
  aux = s/np.sum(s)
  print('...S[0:10] (NORMALIZED to SUM to 100%) = \n', aux[0:10])
  plt.figure(figsize=(10,8))
  xlab = np.arange(pca0, 50+pca0, 1)
  plt.stem(xlab, aux[0+pca0:50+pca0], stem_col, use_line_collection=True)
  plt.title('Run# '+str(idx)+' '+str(subsetInfo['BinNo'][sigIndex])+' PCs (50
 largest, first/largest Not Shown). \n NOTE: Plot Normalized: All PCs add to
 1'+wavstr)
  pch='PCs indexes sorted by magnitude starting from PC='+str(pca0)
  plt.xlabel(pch)
  plt.ylabel('Relative Strengh PC (PC Sum Normalized to 1)');

  plt.figure(figsize=(10,8))
  lam   =  s**2
  PoV   =  np.log(np.cumsum(lam)/np.sum(lam))*10
  plt.plot(np.arange(1,PoV.shape[0]+1), PoV, '-b')
  plt.grid()
  plt.xlabel('Number of PCs', fontsize=16)
  plt.ylabel('log10(PoV)', fontsize=16)
  plt.xlim((1,PoV.shape[0]+1))

  #print('...#%02d'%sigIndex,':','Min =', 10.*np.log10(min(S.fla
t)),'\n.........Max =', 10.*np.log10(max(S.flat)))
  idx += 1;
  # end of for()

print('***DONE!')
```

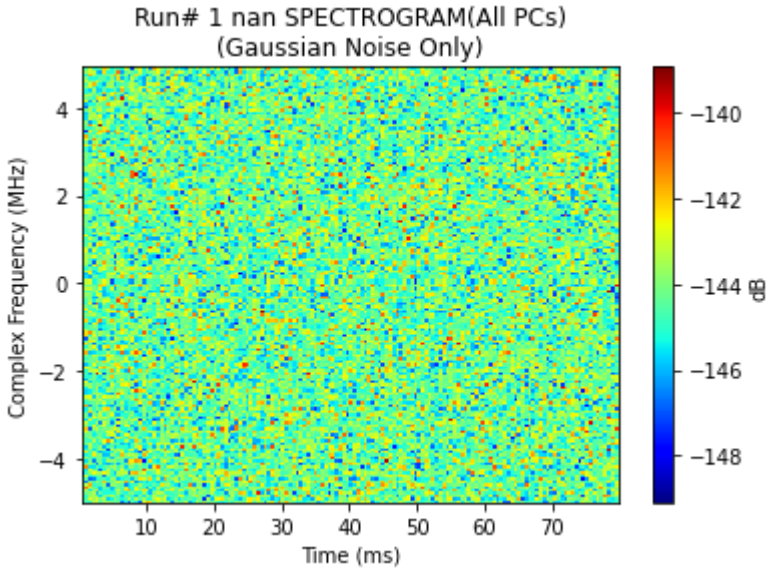
```
***-------------------
***Doing for sigIndex= 0 I= 0
...SNR   : nan
...BinNo : nan
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.3021584638627246e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91983785 0.00127481 0.00122507 0.00119239 0.001175   0.00116176
 0.00114517 0.00113336 0.00112209 0.00109473]
***-------------------
***Doing for sigIndex= 1 I= 1
...SNR   : nan
...BinNo : nan
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  1.9895196601282805e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.92019345 0.00130539 0.00124545 0.00123469 0.00118239 0.00117644
 0.00113607 0.00112823 0.00111364 0.00110824]
***-------------------
***Doing for sigIndex= 35 I= 35
...SNR   : 20.0
...BinNo : P0N#2
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  6.394884621840902e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.9149646  0.00553405 0.00127679 0.00125894 0.00121393 0.00118047
 0.00116793 0.00116124 0.0011562  0.00113433]
***-------------------
***Doing for sigIndex= 58 I= 58
...SNR   : 20.0
...BinNo : Q3N#3
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.9274360713316128e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91477053 0.00274237 0.00259661 0.00142077 0.00139571 0.00132032
 0.00126642 0.00120036 0.0011734  0.00115988]
***-------------------
***Doing for sigIndex= 65 I= 65
...SNR   : 20.0
...BinNo : P0N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.4726887204451486e-12
```

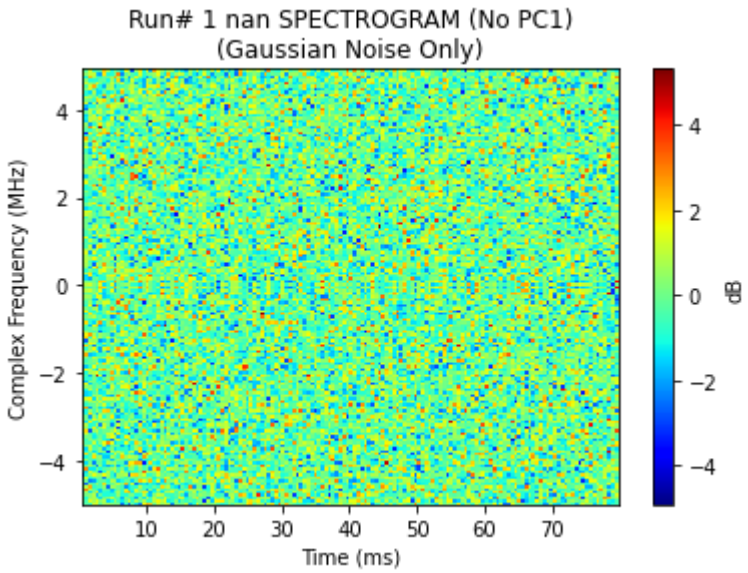
```
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91765343 0.00231691 0.00125611 0.00122822 0.00120347 0.00119546
 0.00117893 0.00116042 0.00114171 0.00111813]
***------------------
***Doing for sigIndex= 68 I= 68
...SNR   : 20.0
...BinNo : Q3N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.1032064978498966e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91388013 0.00394099 0.00156884 0.0014213  0.00131497 0.00127931
 0.00123585 0.00119945 0.00116732 0.00115151]
***------------------
***Doing for sigIndex= 91 I= 91
...SNR   : 20.0
...BinNo : P0N#2
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  4.490630090003833e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91583381 0.00458533 0.00121935 0.00120956 0.0011942  0.00118662
 0.00115026 0.00113951 0.00113306 0.00112921]
***------------------
***Doing for sigIndex= 111 I= 111
...SNR   : 20.0
...BinNo : Q3N#2
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.4726887204451486e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91877696 0.00202446 0.00127082 0.00124709 0.0012271  0.00119706
 0.00117838 0.00115496 0.00114193 0.00112805]
***------------------
***Doing for sigIndex= 114 I= 114
...SNR   : 20.0
...BinNo : P0N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  1.8758328224066645e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91667905 0.00342856 0.00127163 0.00125562 0.00122589 0.00120123
 0.00118848 0.00117614 0.0011548  0.00113471]
***------------------
***Doing for sigIndex= 115 I= 115
...SNR   : 20.0
...BinNo : P0N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
```

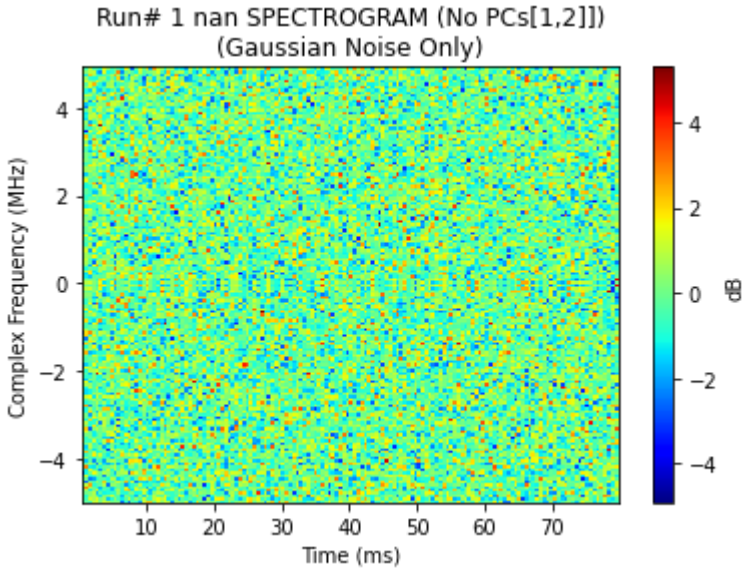
```
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  1.9610979506978765e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91587187 0.00375527 0.0012744  0.00126157 0.00121259 0.00119711
 0.00115284 0.00112505 0.00112126 0.00111307]
***------------------
***Doing for sigIndex= 117 I= 117
...SNR   : 20.0
...BinNo : Q3N#2
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  4.320099833421409e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91427553 0.00551098 0.00147408 0.00126767 0.00121866 0.00118554
 0.00116914 0.00116462 0.00113491 0.00111884]
***------------------
***Doing for sigIndex= 119 I= 119
...SNR   : 20.0
...BinNo : P0N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.1316282072803006e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91801786 0.00227813 0.00129252 0.00125248 0.00122077 0.0012131
 0.00117509 0.00115719 0.00113627 0.00112587]
***------------------
***Doing for sigIndex= 124 I= 124
...SNR   : 20.0
...BinNo : Q3N#2
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  1.9042545318370685e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91772436 0.00263085 0.00123671 0.00123338 0.00121667 0.00119499
 0.00117821 0.00115177 0.00114179 0.0011146 ]
***------------------
***Doing for sigIndex= 125 I= 125
...SNR   : 20.0
...BinNo : Q3N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.2168933355715126e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91188267 0.00824157 0.00129084 0.00126251 0.00122086 0.00120967
 0.00118513 0.00116208 0.0011385  0.00110954]
***------------------
***Doing for sigIndex= 139 I= 139
...SNR   : 20.0
```

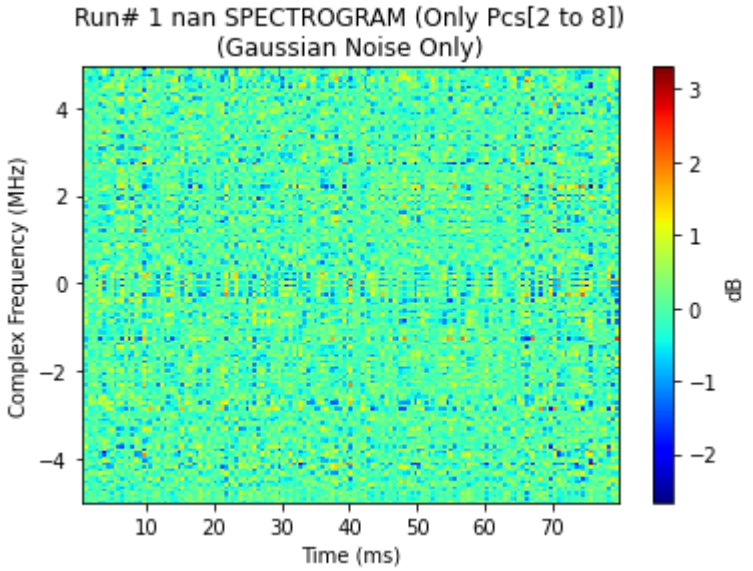
```
...BinNo : P0N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.0747847884194925e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91678175 0.00352307 0.00124714 0.00123706 0.00120911 0.0011934
 0.00116897 0.00114408 0.00113639 0.00111789]
***------------------
***Doing for sigIndex= 141 I= 141
...SNR   : 20.0
...BinNo : P0N#2
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.2737367544323206e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91503501 0.00518061 0.00127501 0.00122063 0.00120676 0.00117732
 0.00116205 0.00114086 0.0011359  0.00111901]
***------------------
***Doing for sigIndex= 147 I= 147
...SNR   : 20.0
...BinNo : Q3N#3
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.1884716261411086e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91571179 0.00187964 0.00181203 0.00138379 0.0012718  0.00125069
 0.0012272  0.00119967 0.00118466 0.00116973]
***------------------
***Doing for sigIndex= 167 I= 167
...SNR   : 20.0
...BinNo : Q3N#1
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  5.286437954055145e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91409672 0.0046742  0.00150484 0.00130632 0.00126942 0.00120999
 0.00119494 0.00117879 0.00116651 0.00116493]
***------------------
***Doing for sigIndex= 178 I= 178
...SNR   : 20.0
...BinNo : Q3N#3
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.1316282072803006e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91731228 0.00148496 0.00144127 0.00129005 0.00127702 0.0012451
 0.00121459 0.00118883 0.00116097 0.00113436]
```

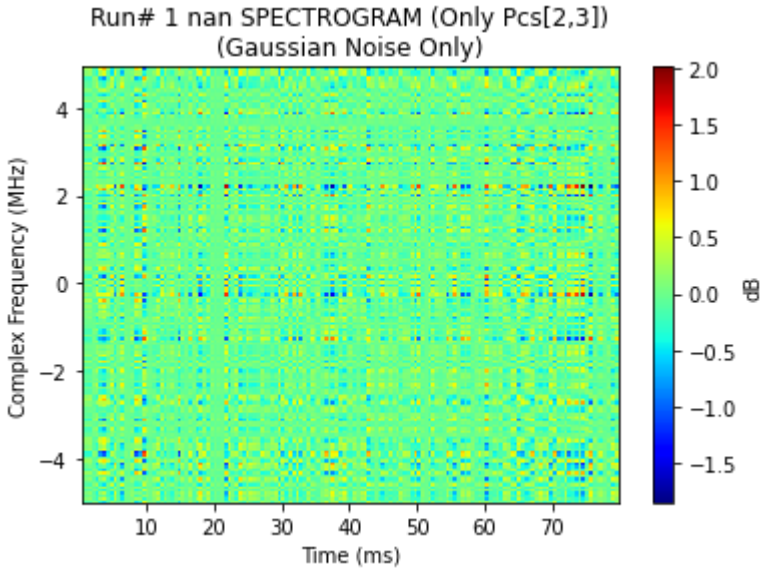
```
***-------------------
***Doing for sigIndex= 183 I= 183
...SNR    : 20.0
...BinNo : Q3N#2
...S.shape= (150, 150)
...U.shape= (150, 150)
...S.shape= (150,)
...Vh.shape (150, 150)
...CHECKDIFFMAT (ORIG vs U.diag(S).Vh):  2.2168933355715126e-12
...S[0:10] (NORMALIZED to SUM to 100%) =
 [0.91819514 0.00143753 0.00135515 0.00127837 0.00125573 0.00122595
 0.00120015 0.00117571 0.00116309 0.00113568]
***DONE!
```

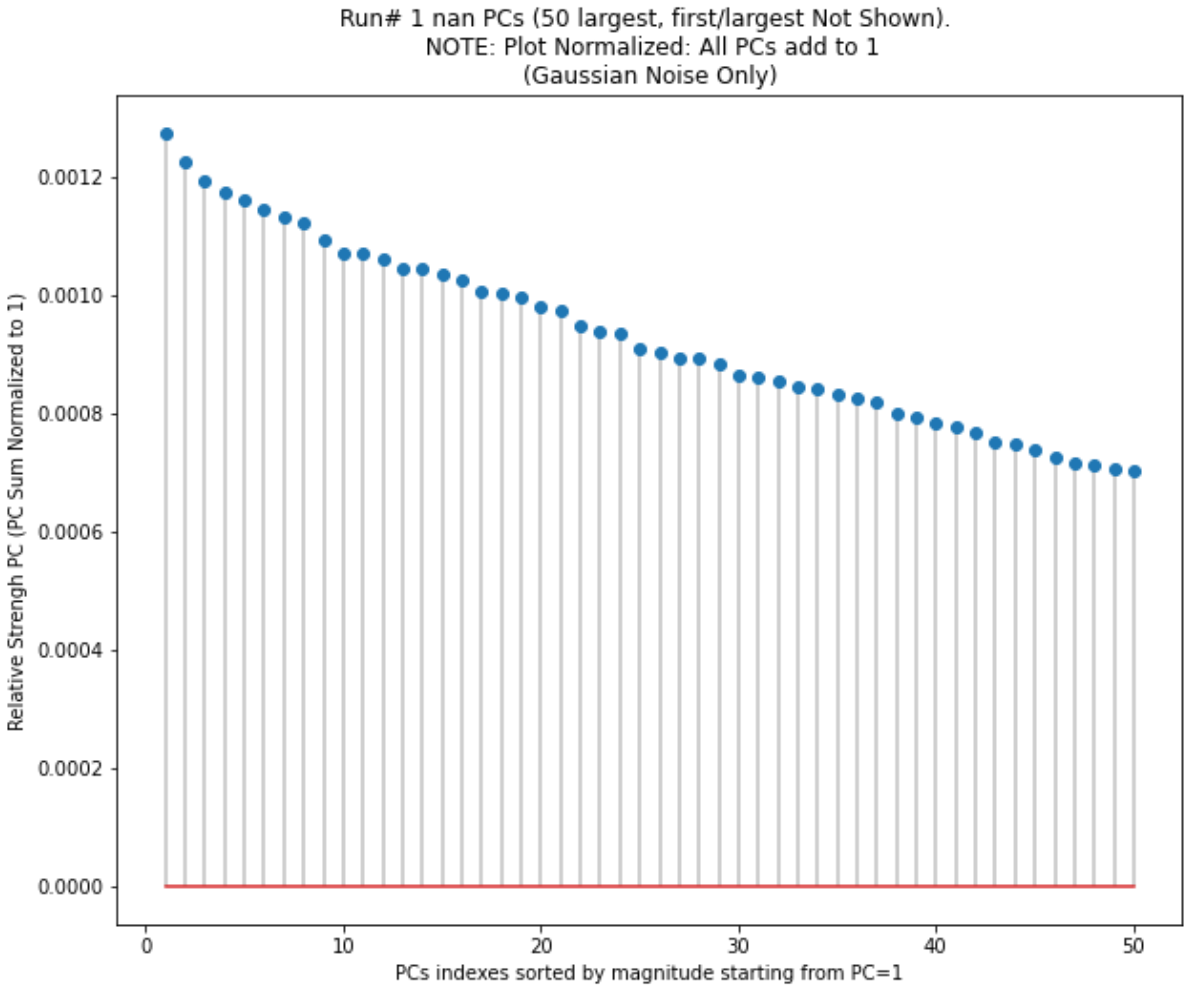


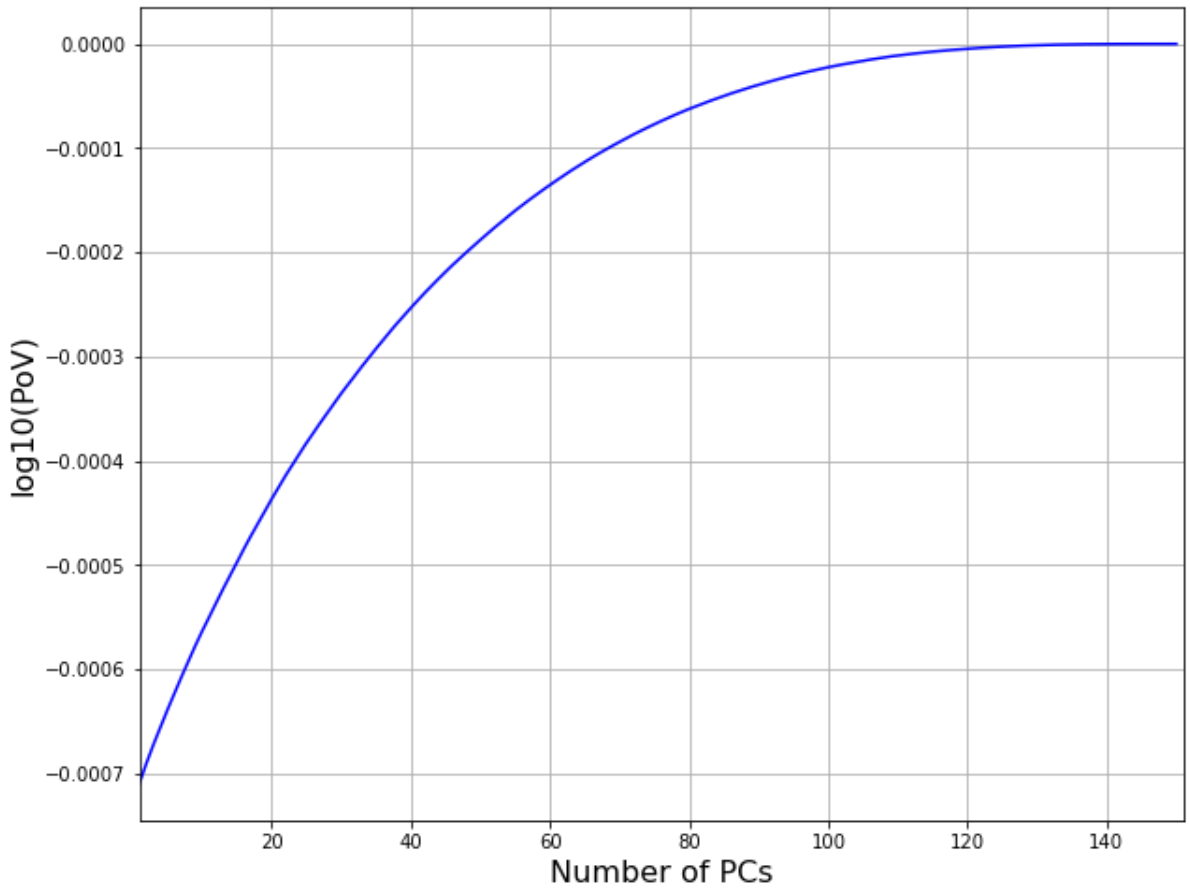


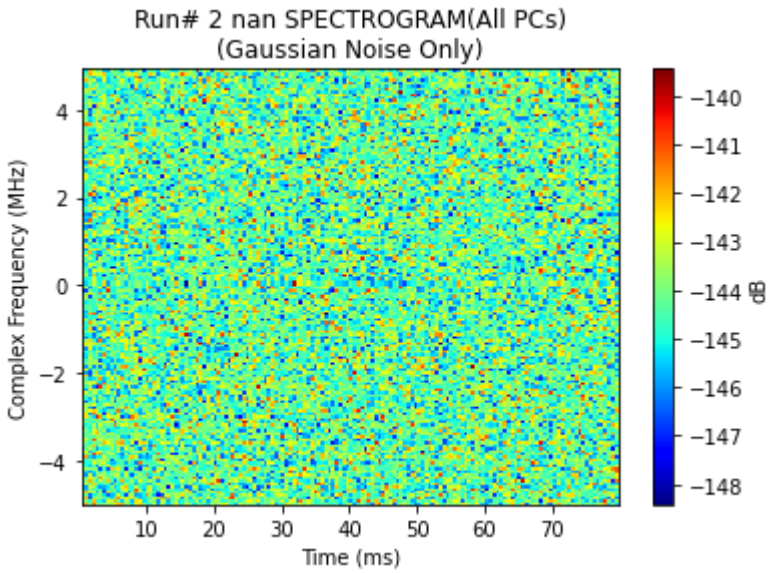

Run# 1 nan SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

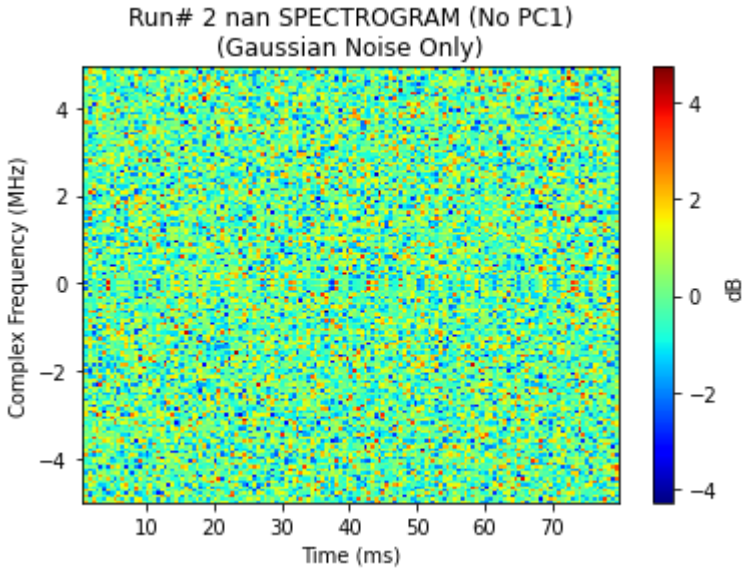

Run# 1 nan SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

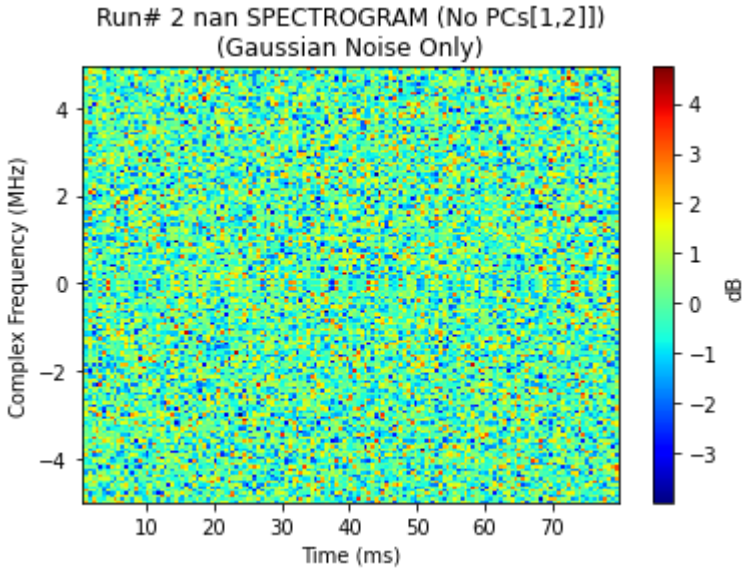

Run# 1 nan SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

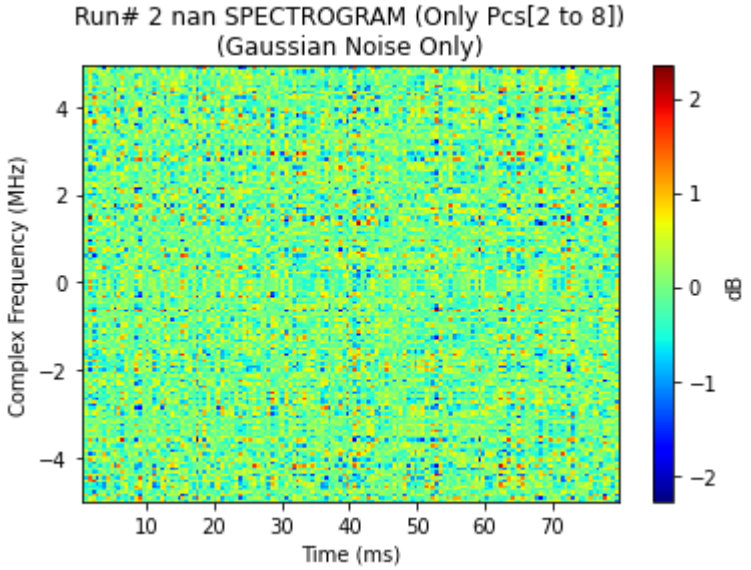

Run# 1 nan PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise Only)
Relative Strengh PC (PC Sum Normalized to 1)
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
10
20
30
40
50
PCs indexes sorted by magnitude starting from PC=1

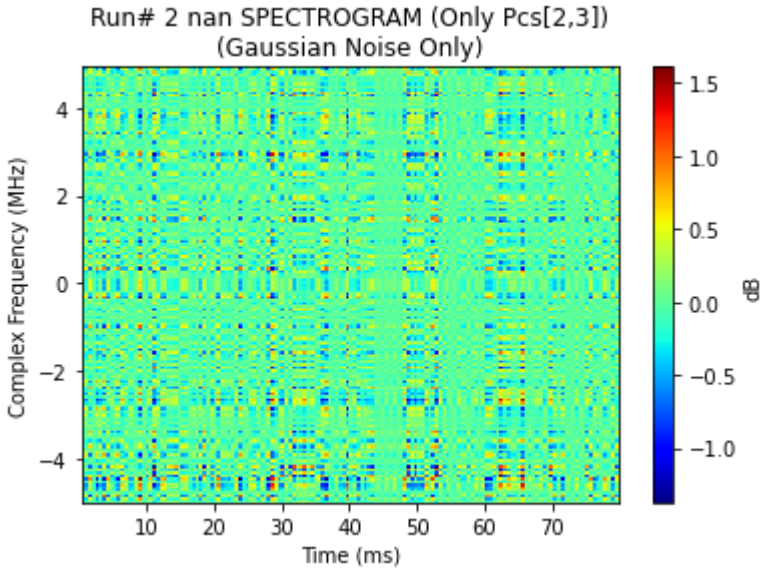

log10(PoV)
0.0000
−0.0001
−0.0002
−0.0003
−0.0004
−0.0005
−0.0006
−0.0007
20
40
60
80
100
120
140
Number of PCs

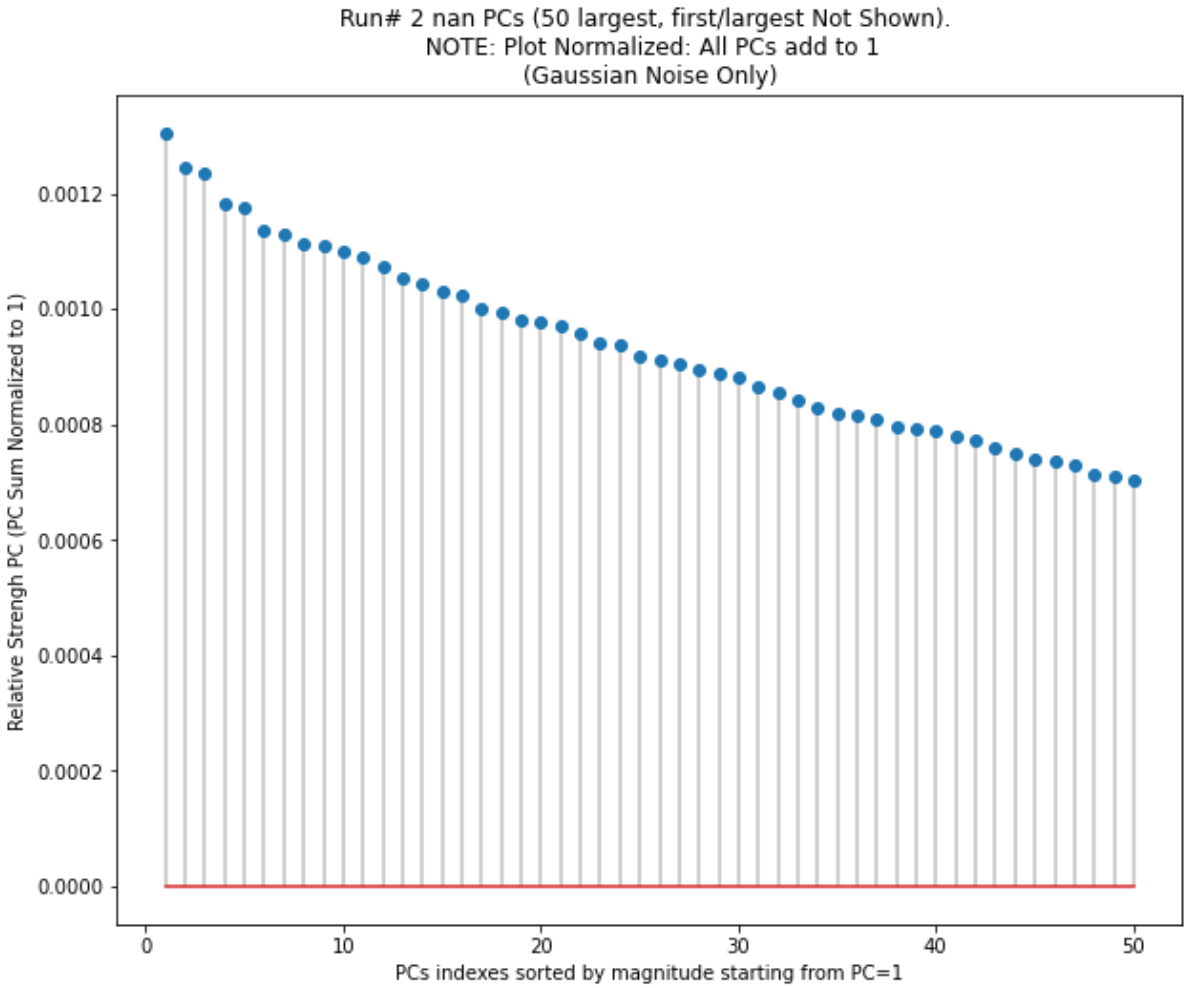

Run# 2 nan SPECTROGRAM(All PCs)
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

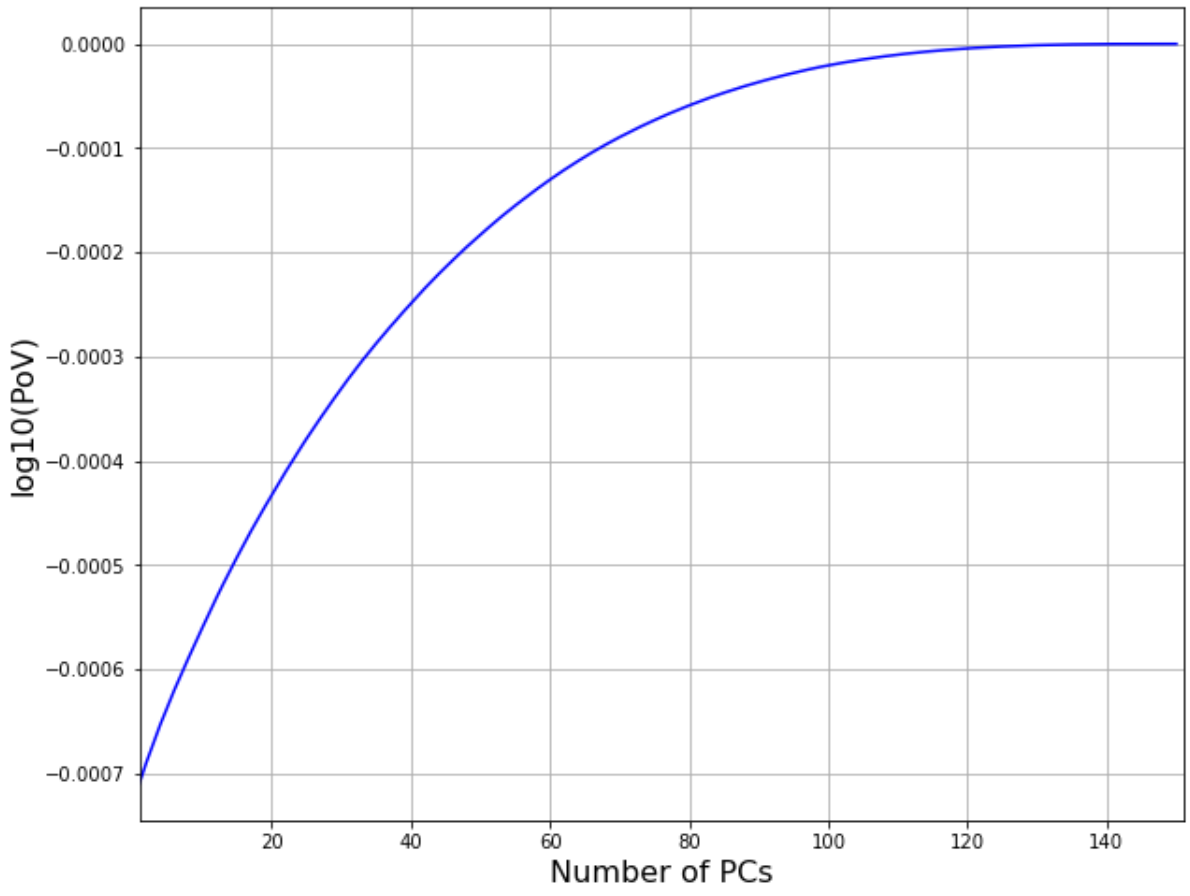

Run# 2 nan SPECTROGRAM (No PC1)
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

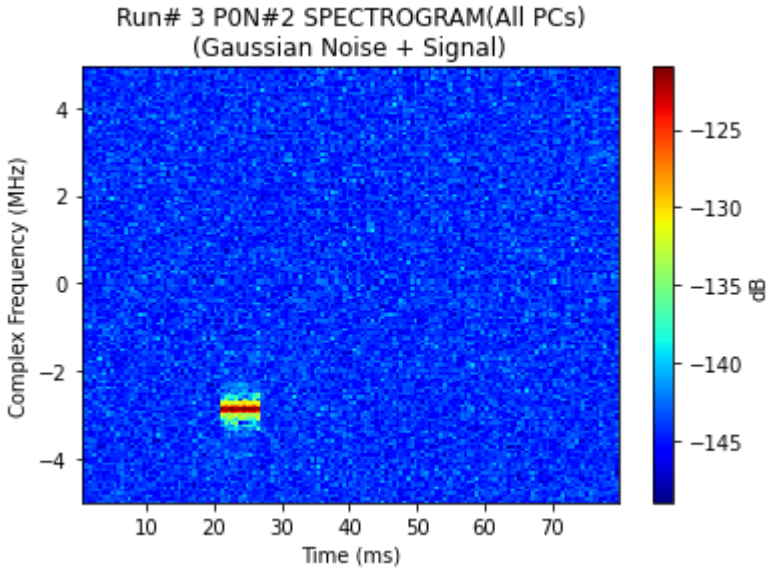

Run# 2 nan SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

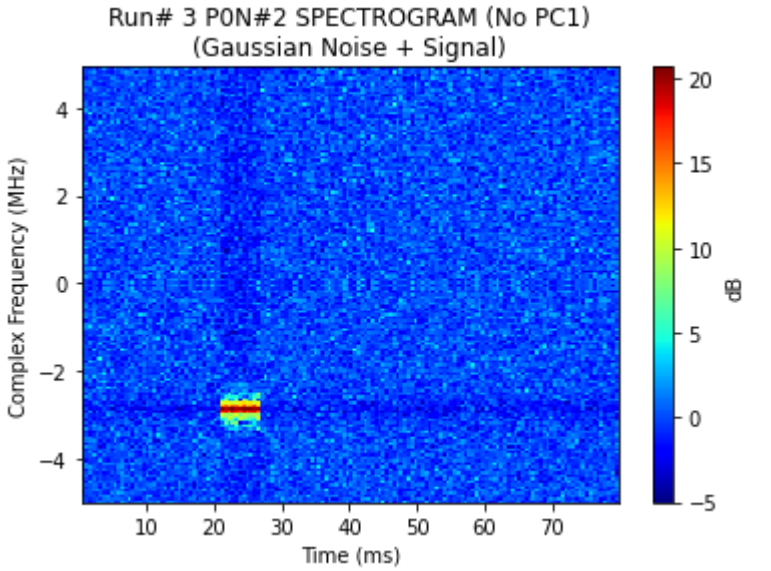

Run# 2 nan SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

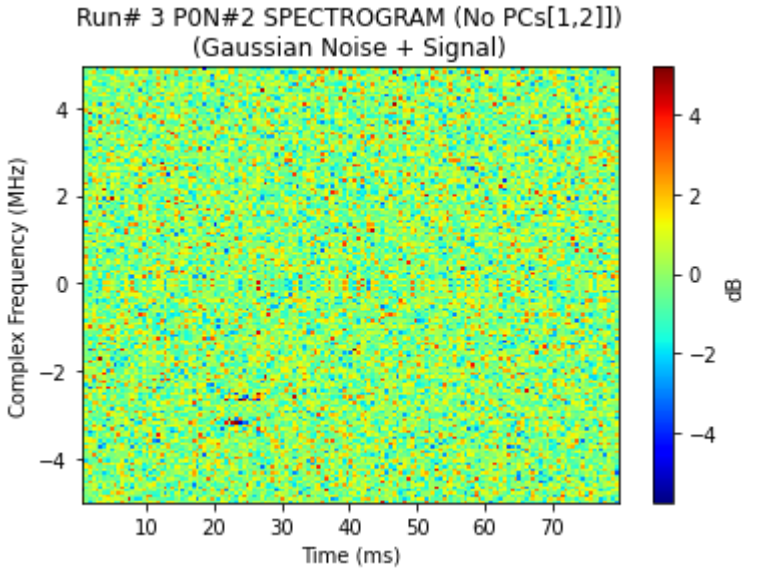

Run# 2 nan SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise Only)
Complex Frequency (MHz)
Time (ms)
dB

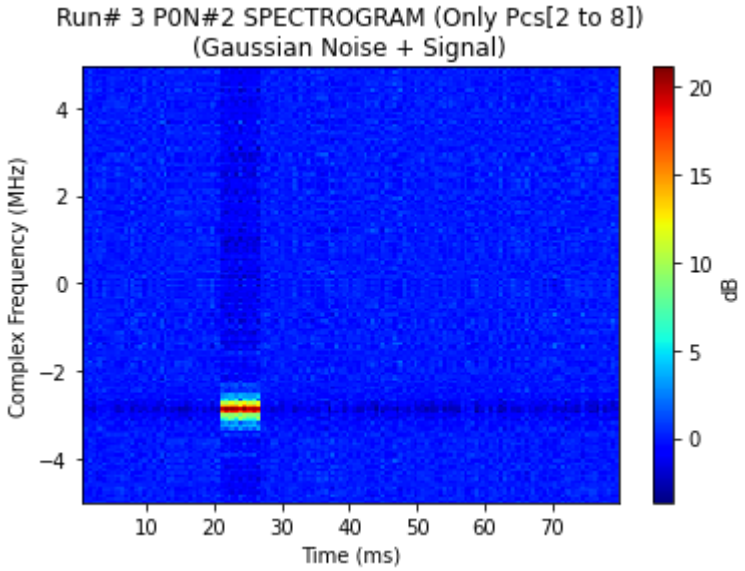

Run# 2 nan PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise Only)
Relative Strengh PC (PC Sum Normalized to 1)
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
10
20
30
40
50
PCs indexes sorted by magnitude starting from PC=1

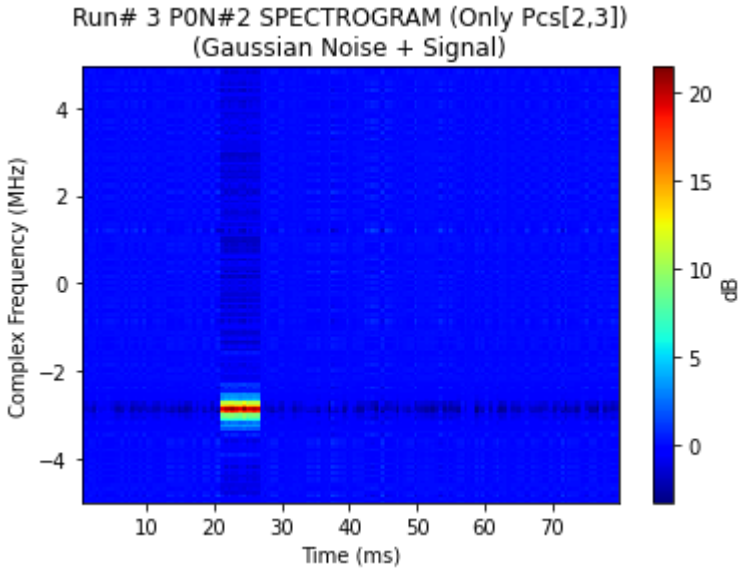

log10(PoV)
0.0000
−0.0001
−0.0002
−0.0003
−0.0004
−0.0005
−0.0006
−0.0007
20
40
60
80
100
120
140
Number of PCs

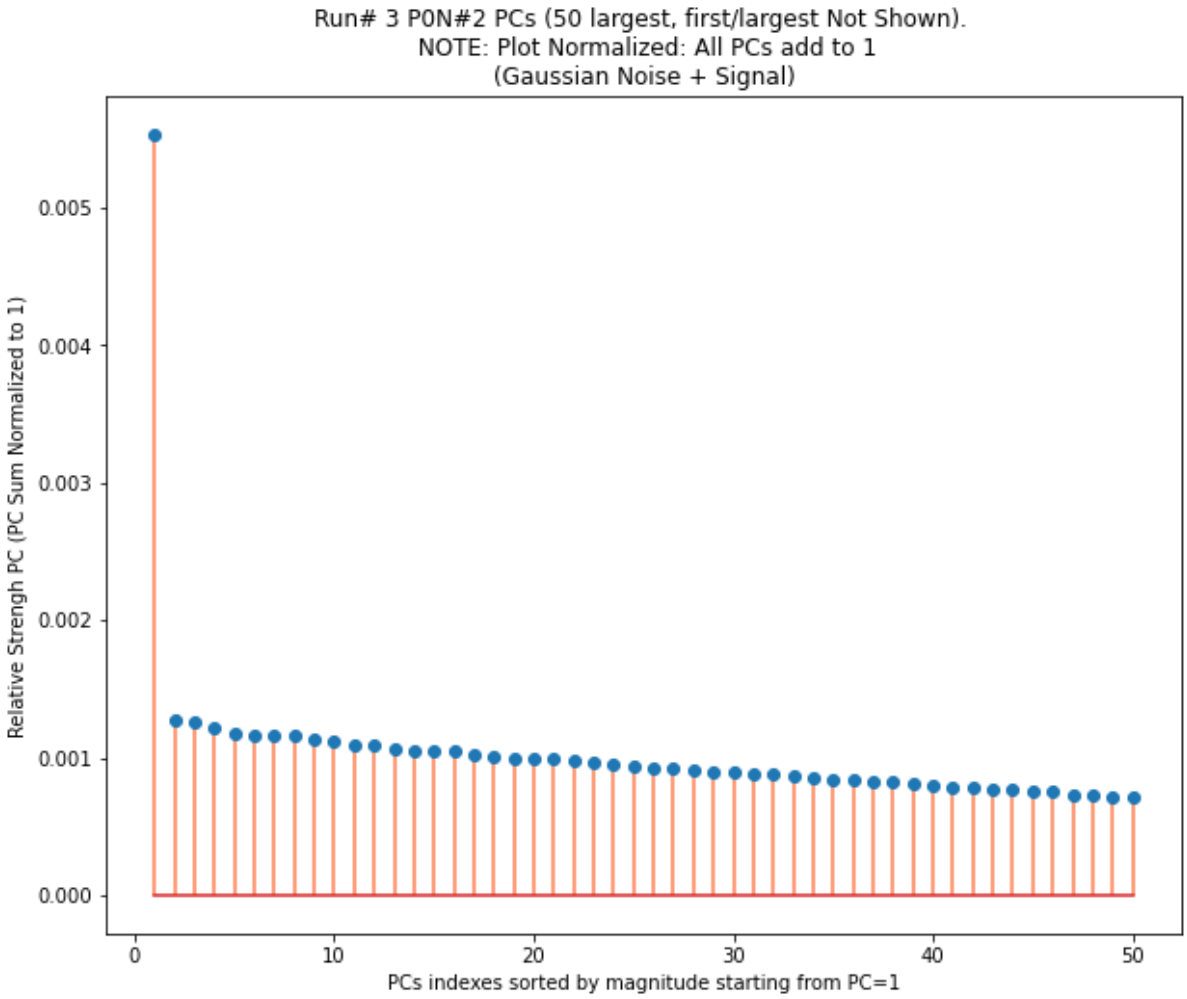

Run# 3 P0N#2 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

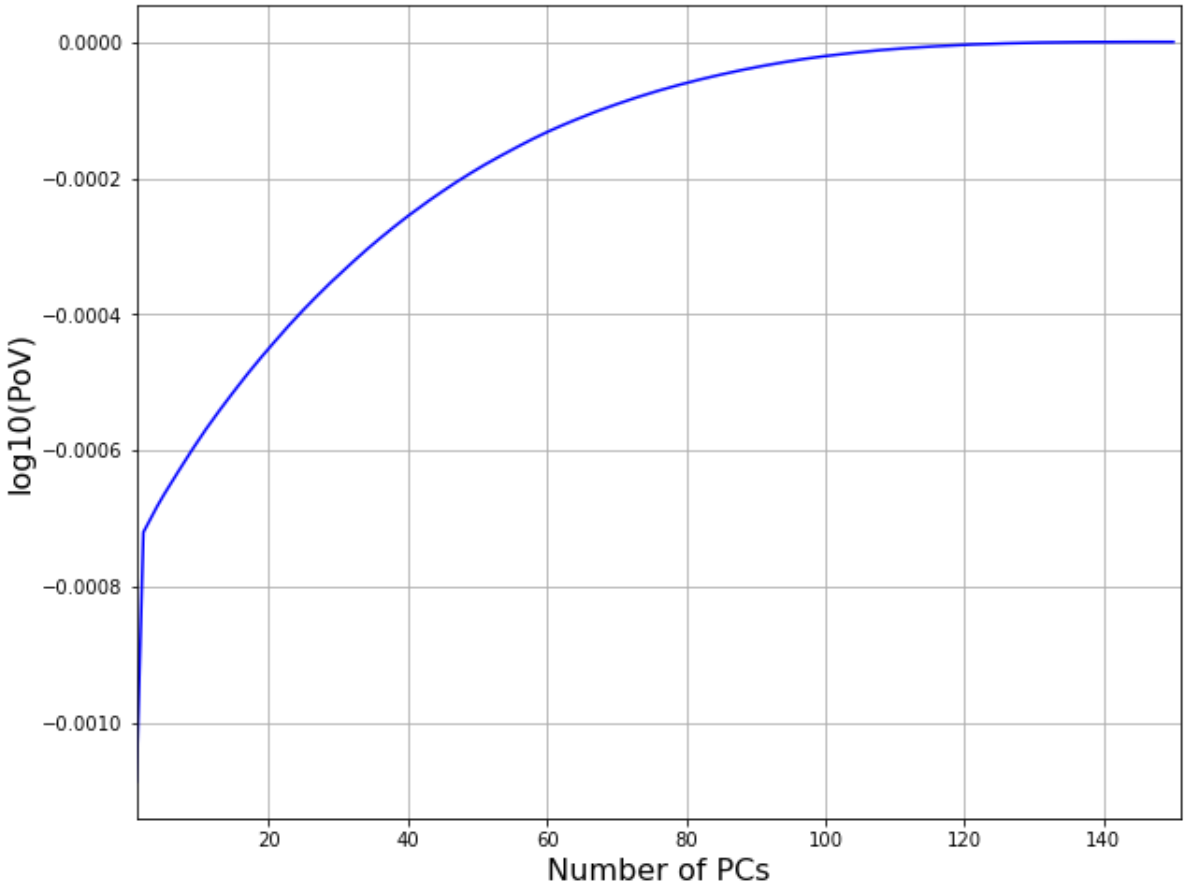

Run# 3 P0N#2 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

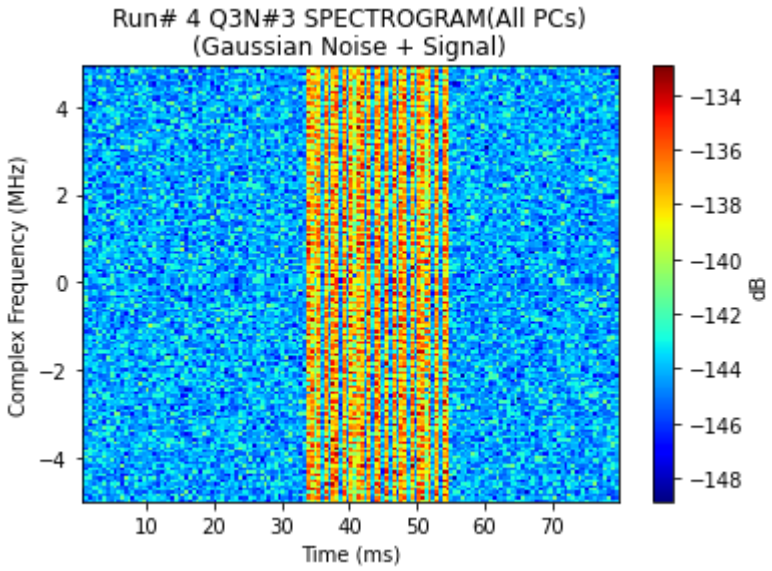

Run# 3 P0N#2 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

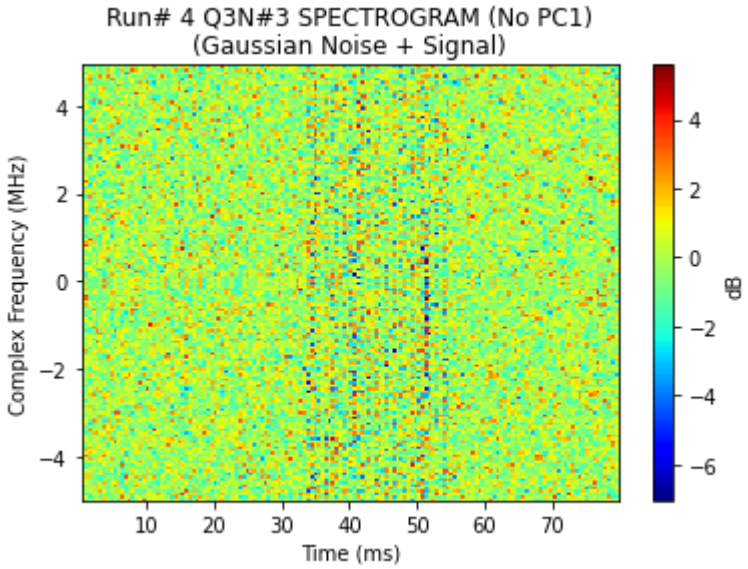

Run# 3 P0N#2 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

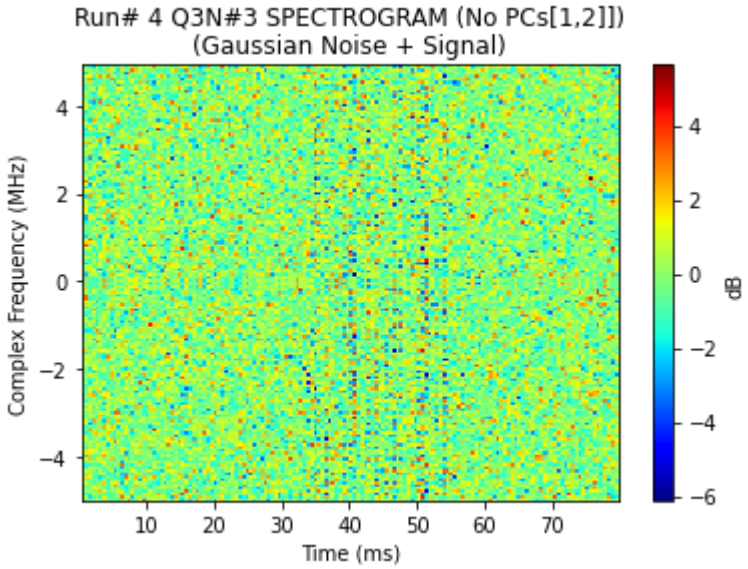

Run# 3 P0N#2 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

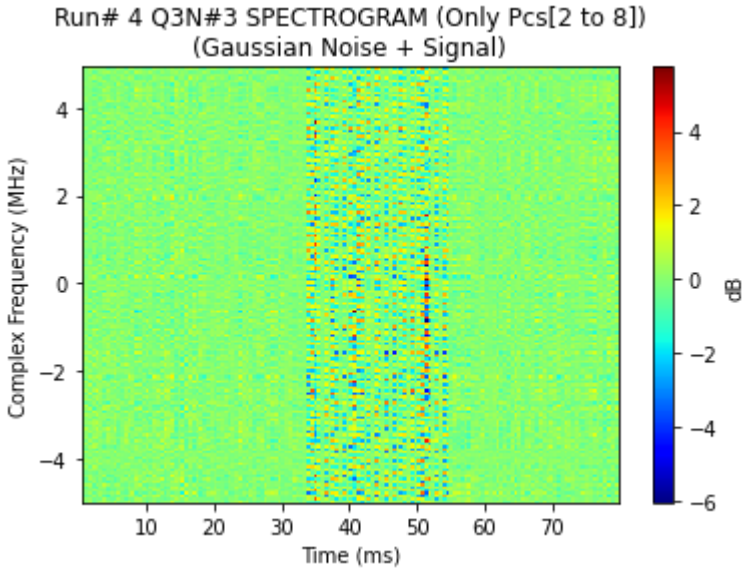

Run# 3 P0N#2 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
0.005
0.004
0.003
0.002
0.001
0.000
0
10
20
30
40
50
PCs indexes sorted by magnitude starting from PC=1

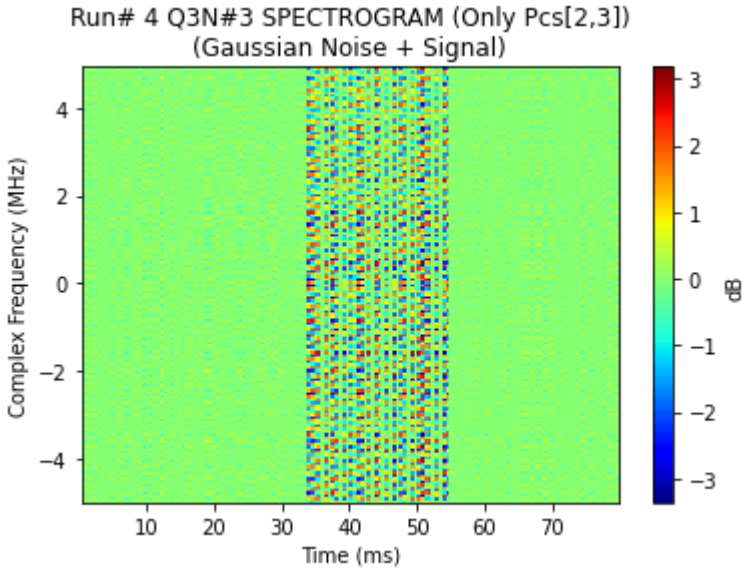

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

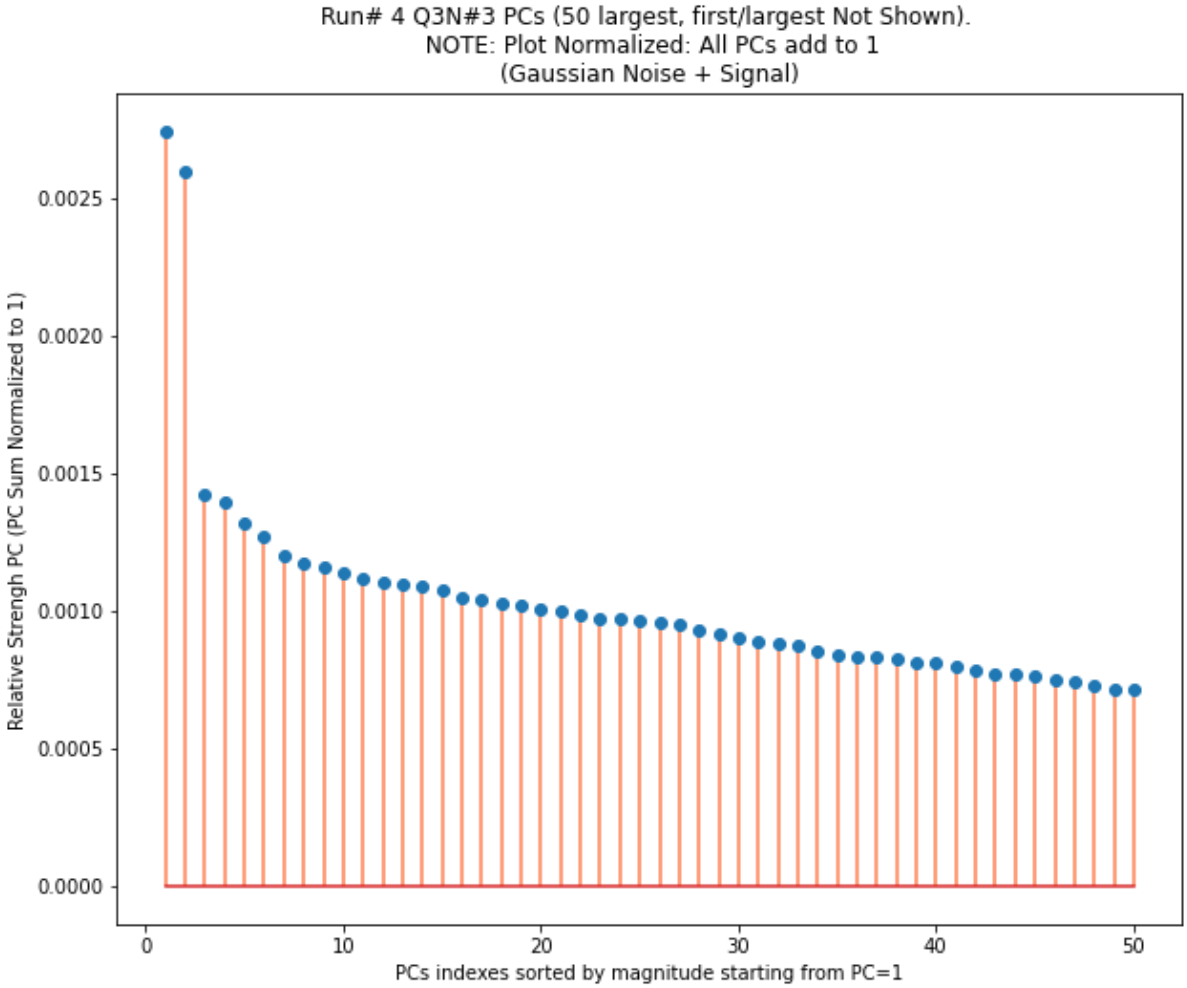

Run# 4 Q3N#3 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−134
−136
−138
−140
−142
−144
−146
−148
dB

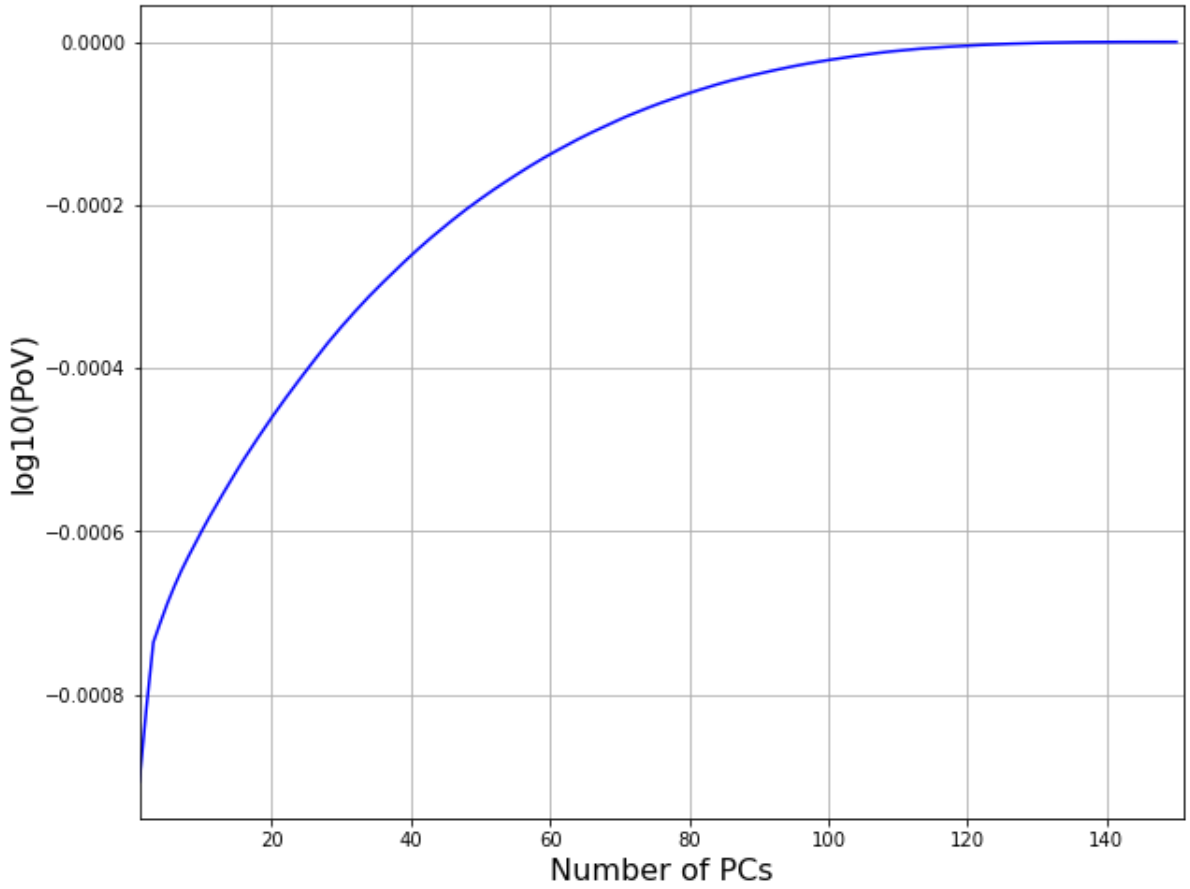

Run# 4 Q3N#3 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

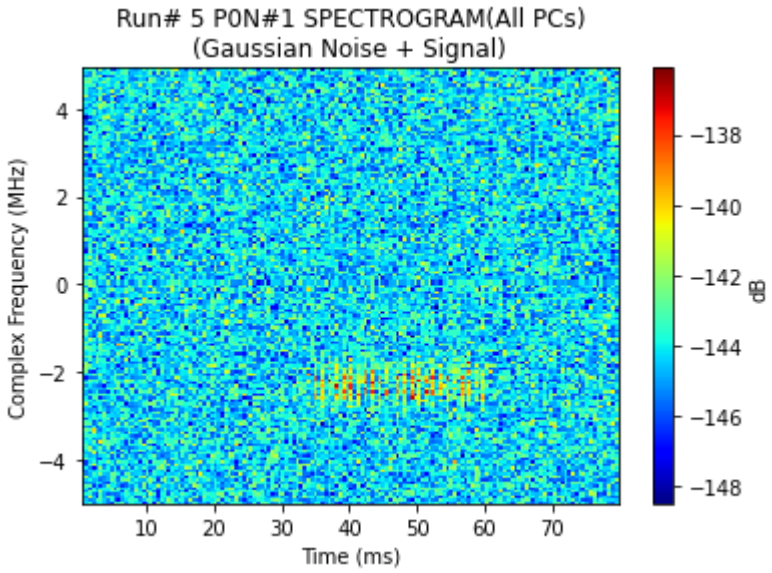

Run# 4 Q3N#3 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

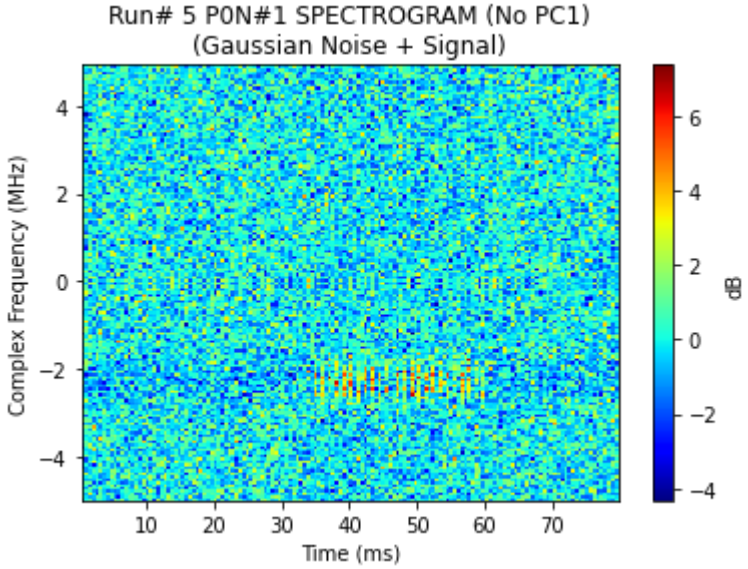

Run# 4 Q3N#3 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

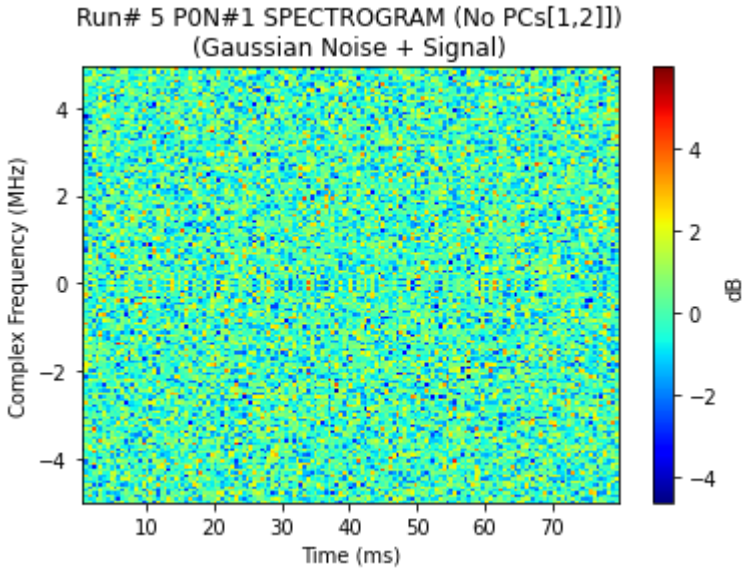

Run# 4 Q3N#3 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

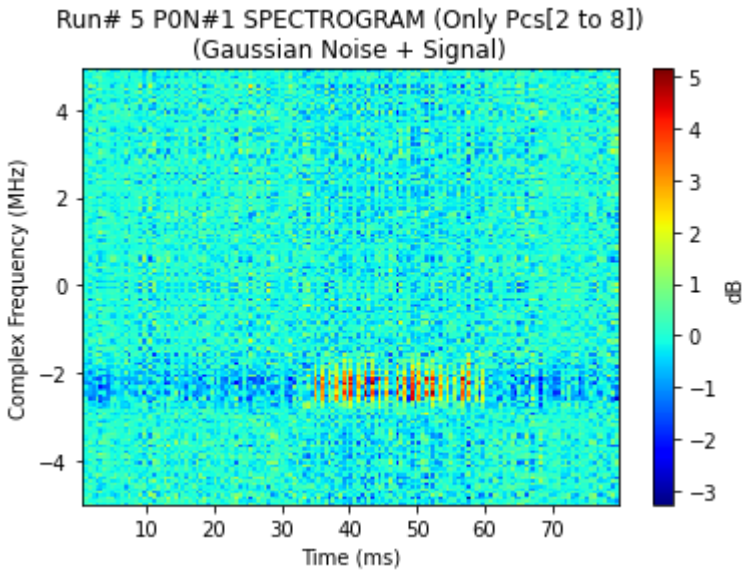

Run# 4 Q3N#3 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

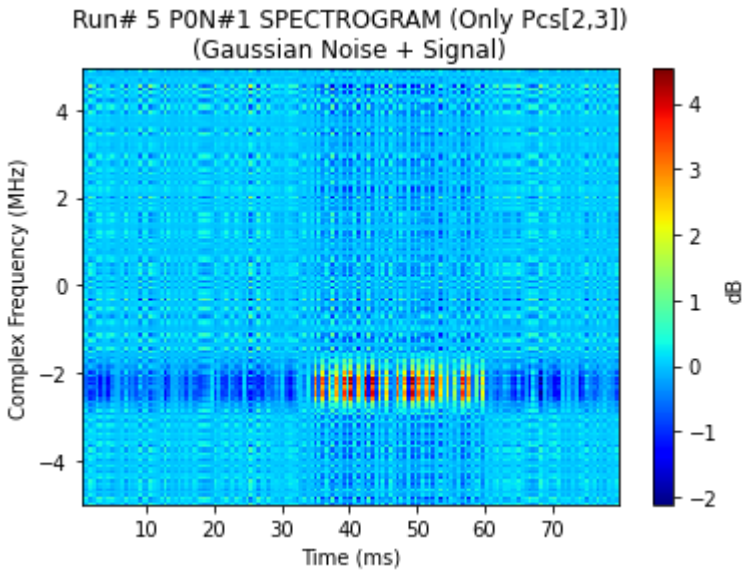

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

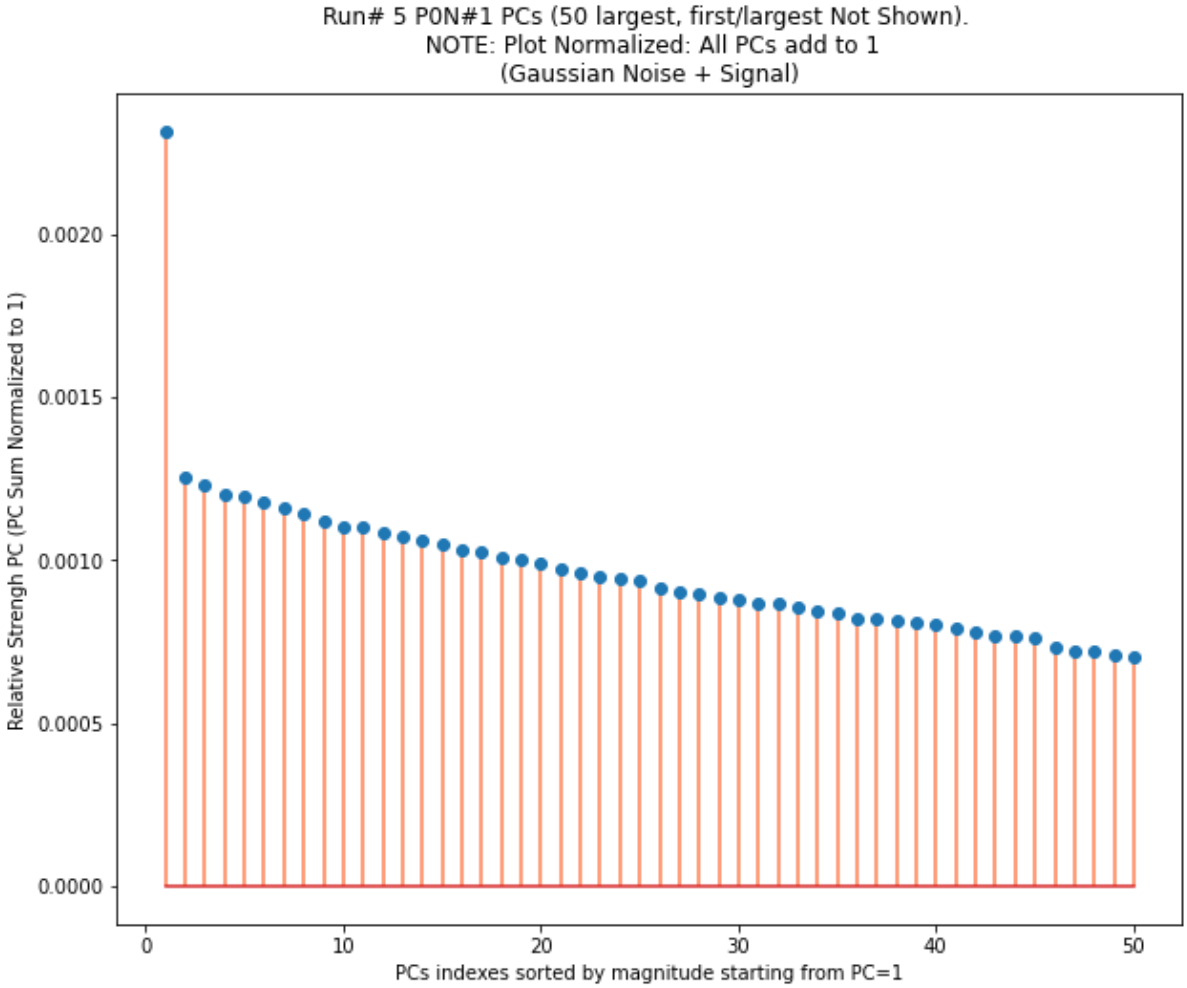

Run# 5 P0N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−138
−140
−142
−144
−146
−148
dB

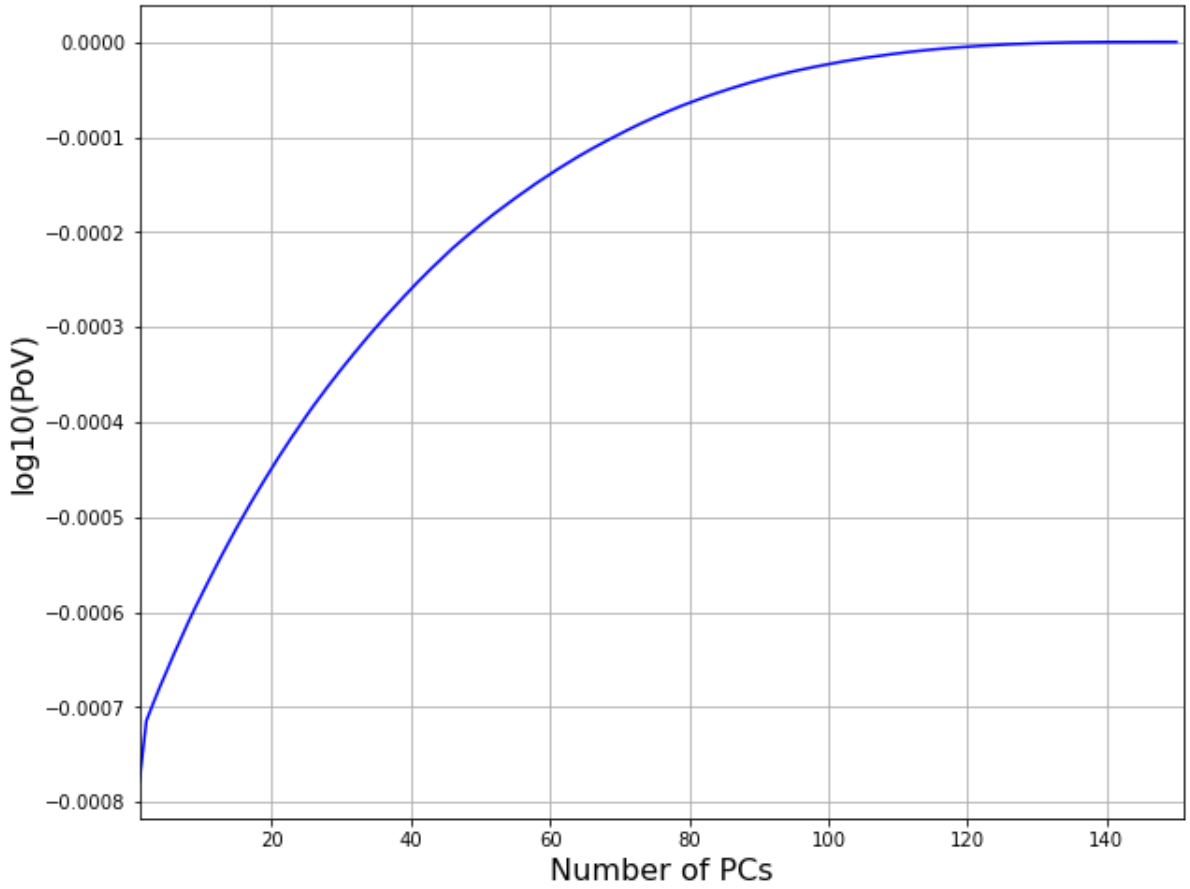

Run# 5 P0N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

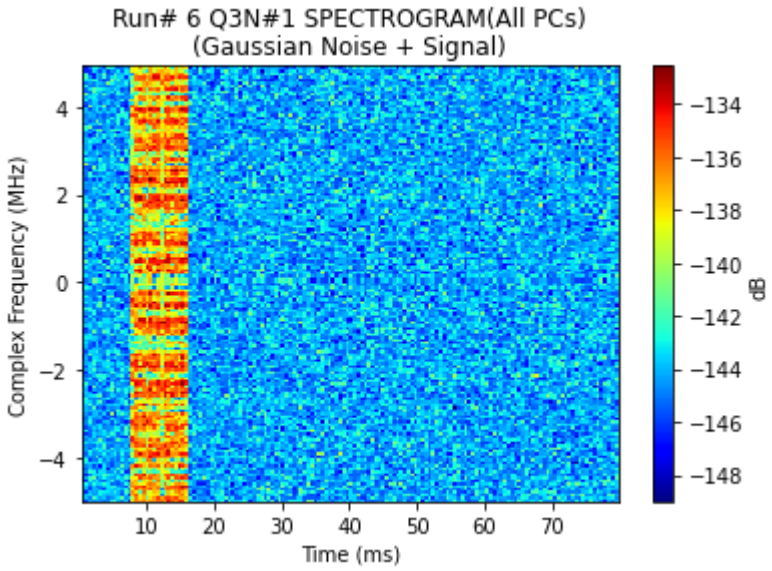

Run# 5 P0N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

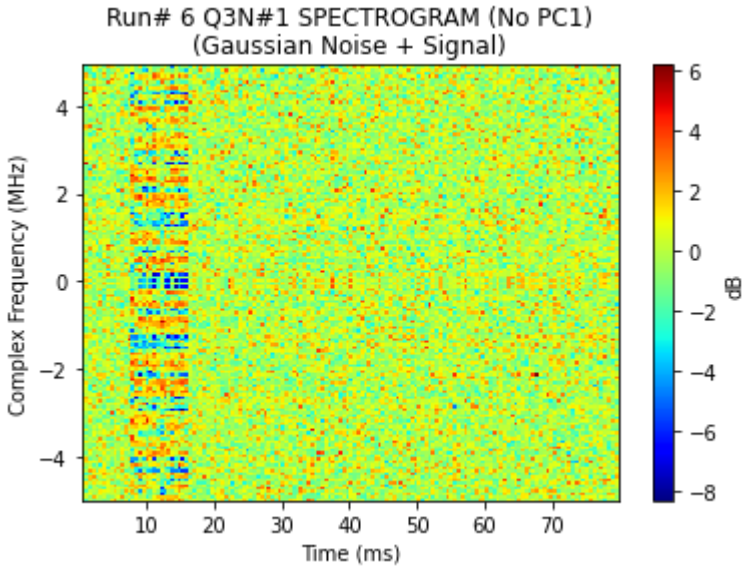

Run# 5 P0N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

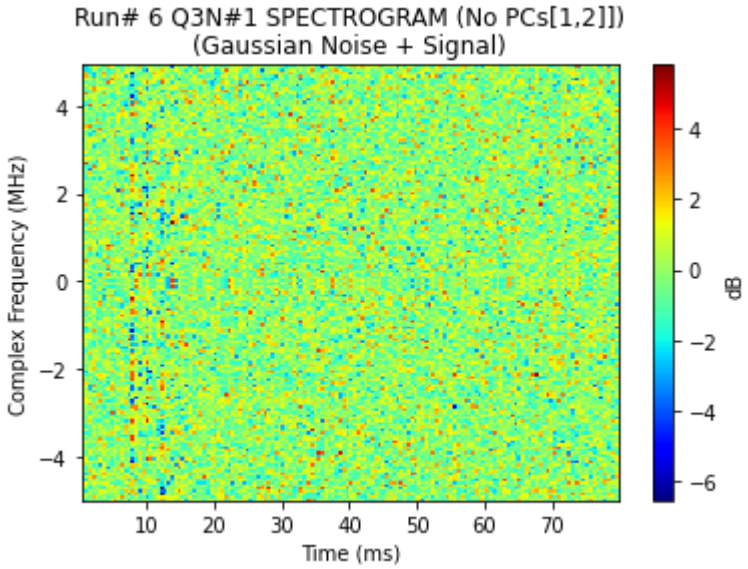

Run# 5 P0N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

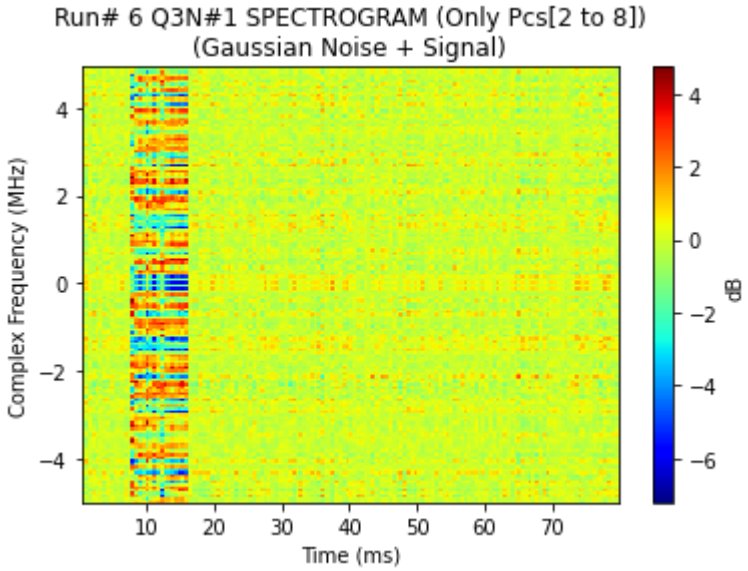

Run# 5 P0N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

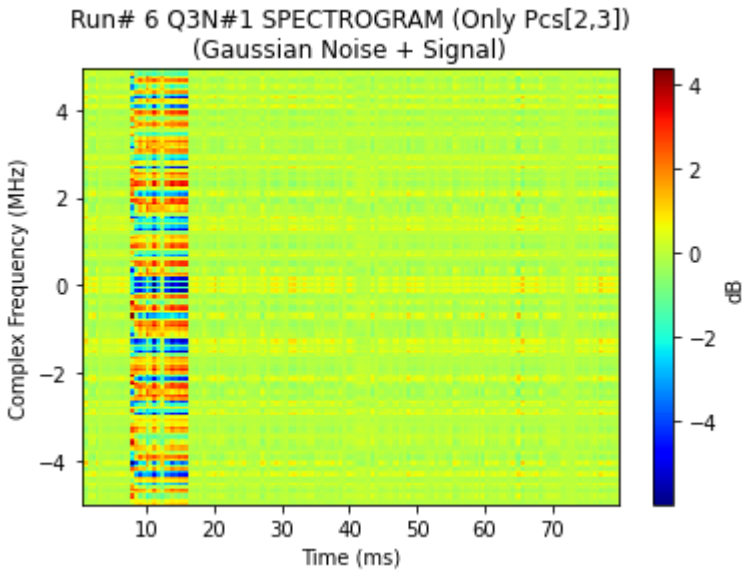

0.0000
−0.0001
−0.0002
−0.0003
−0.0004
−0.0005
−0.0006
−0.0007
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

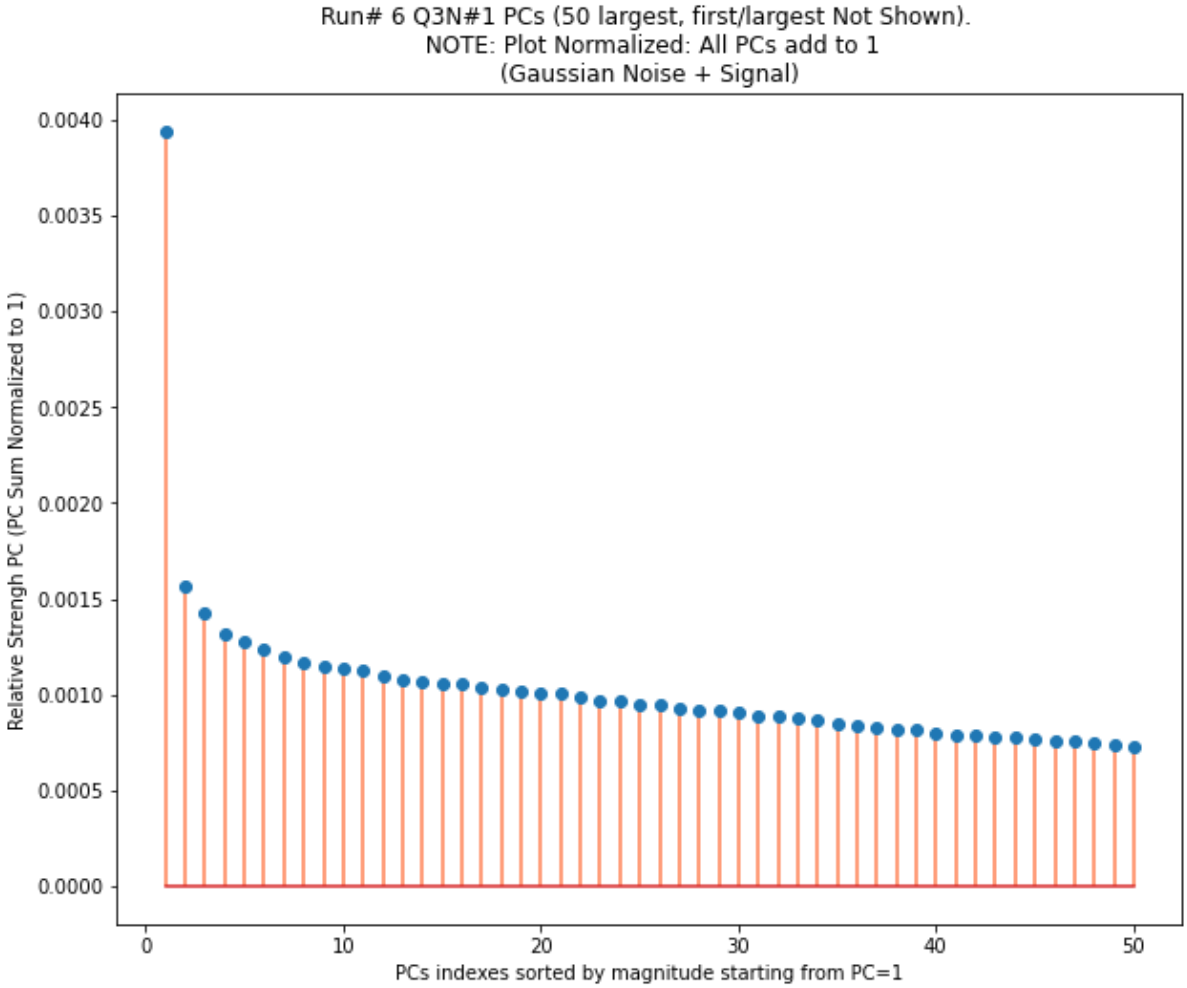

Run# 6 Q3N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−134
−136
−138
−140
−142
−144
−146
−148
dB

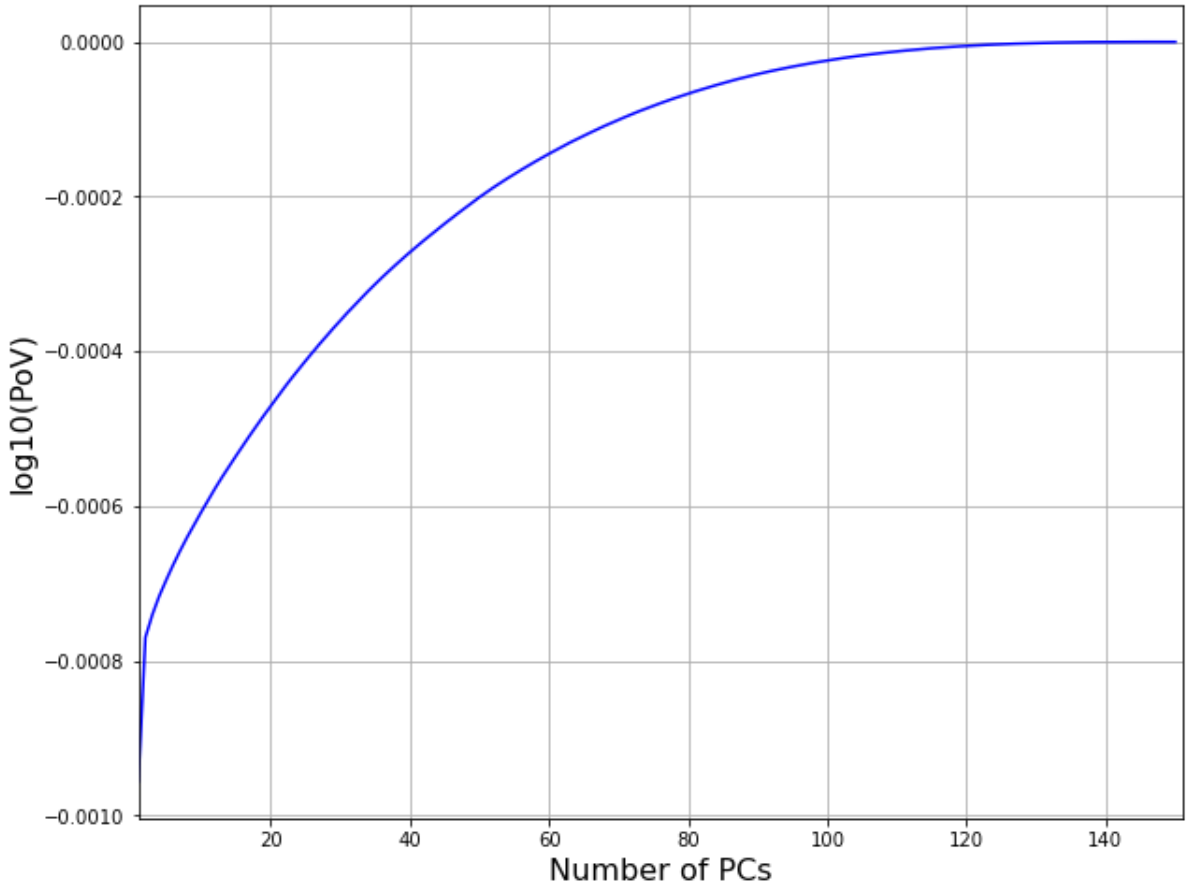

Run# 6 Q3N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

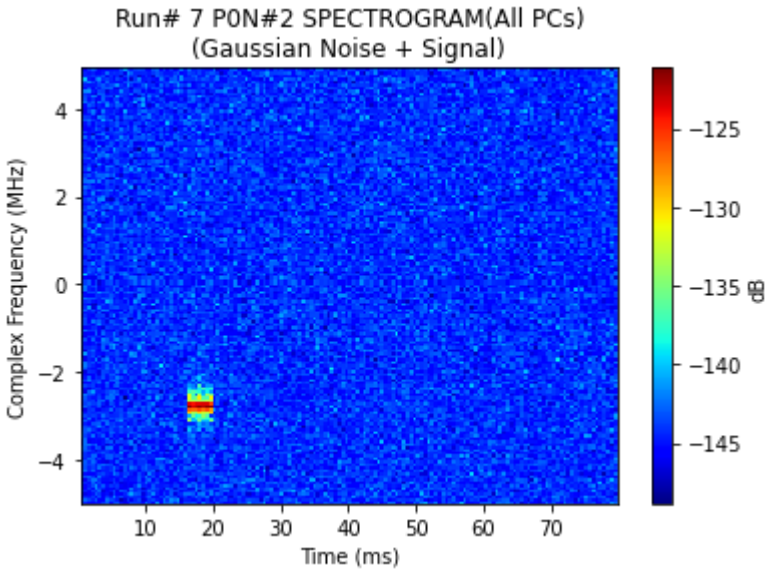

Run# 6 Q3N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

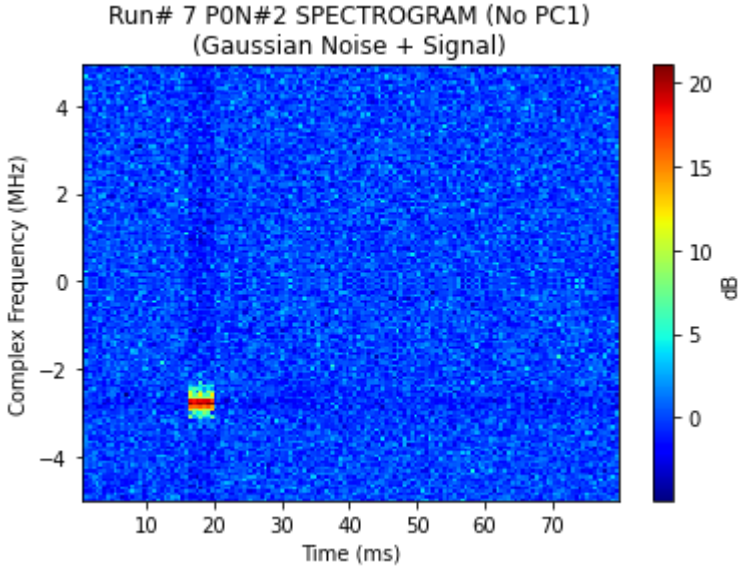

Run# 6 Q3N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

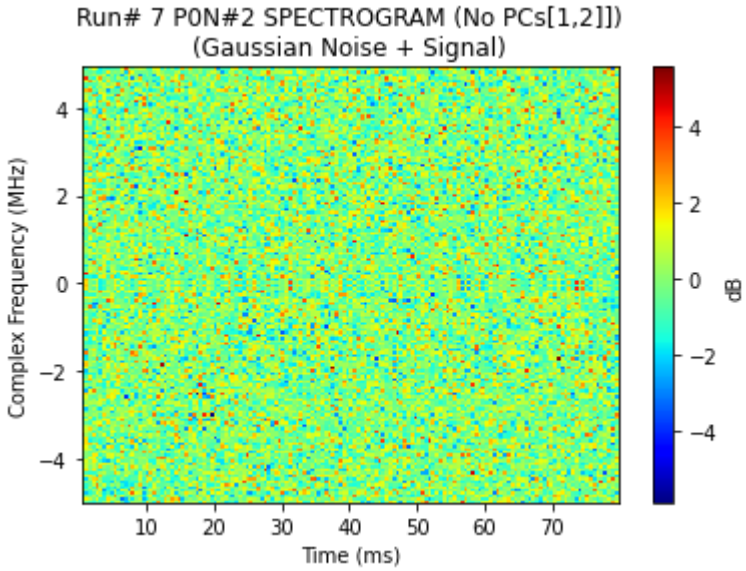

Run# 6 Q3N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

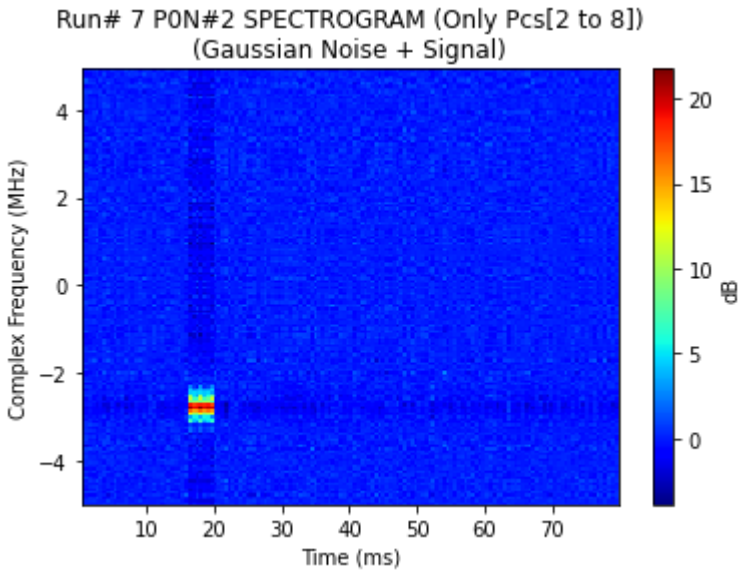

Run# 6 Q3N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

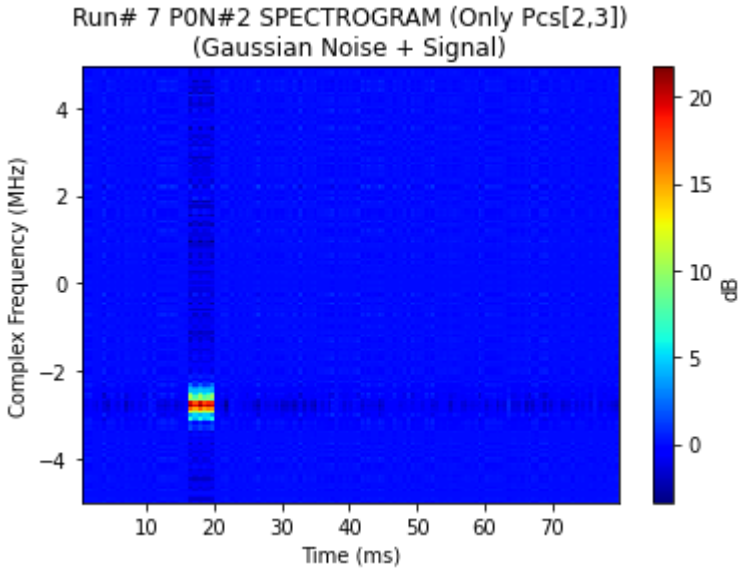

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

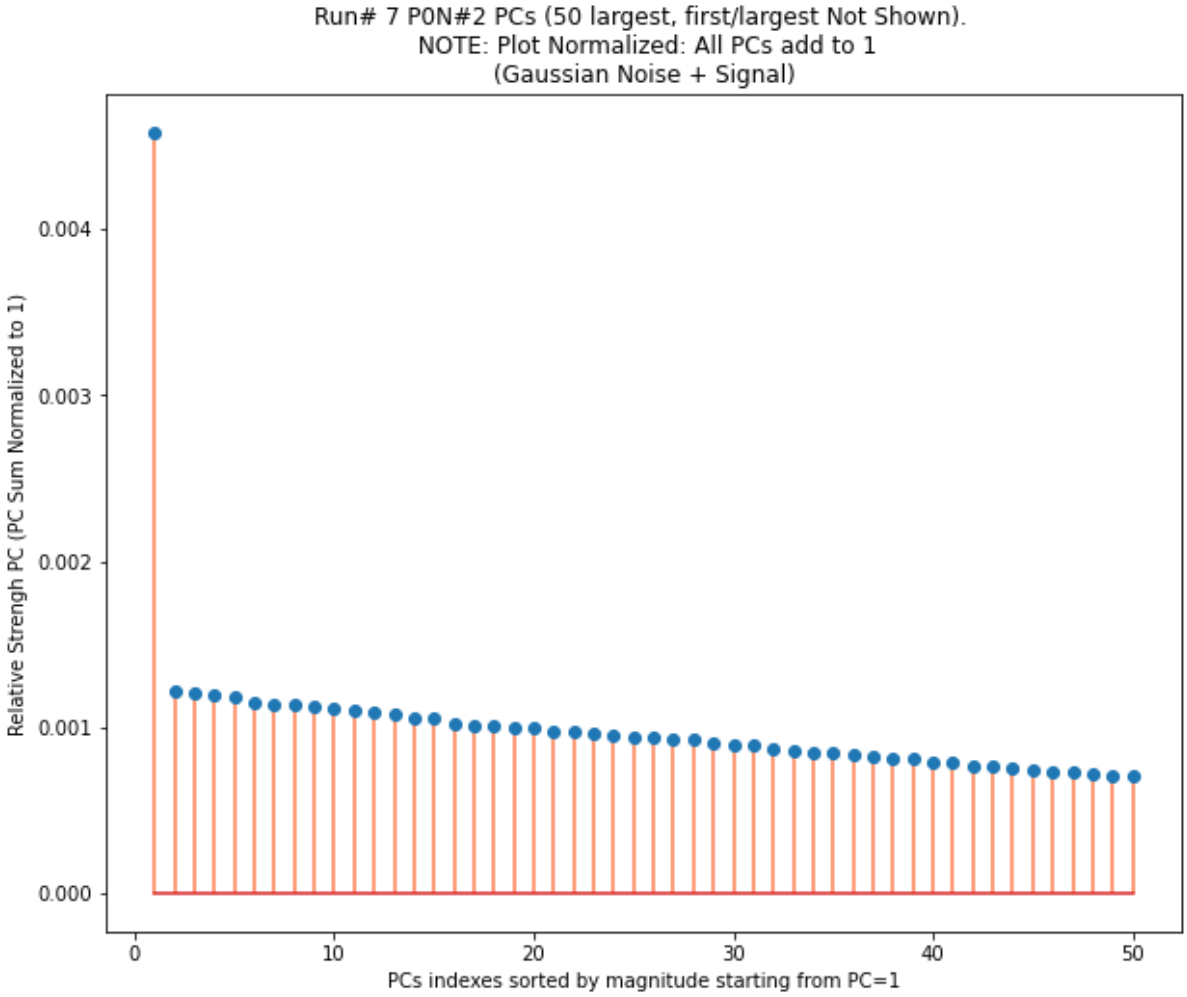

Run# 7 P0N#2 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−125
−130
−135
−140
−145
dB

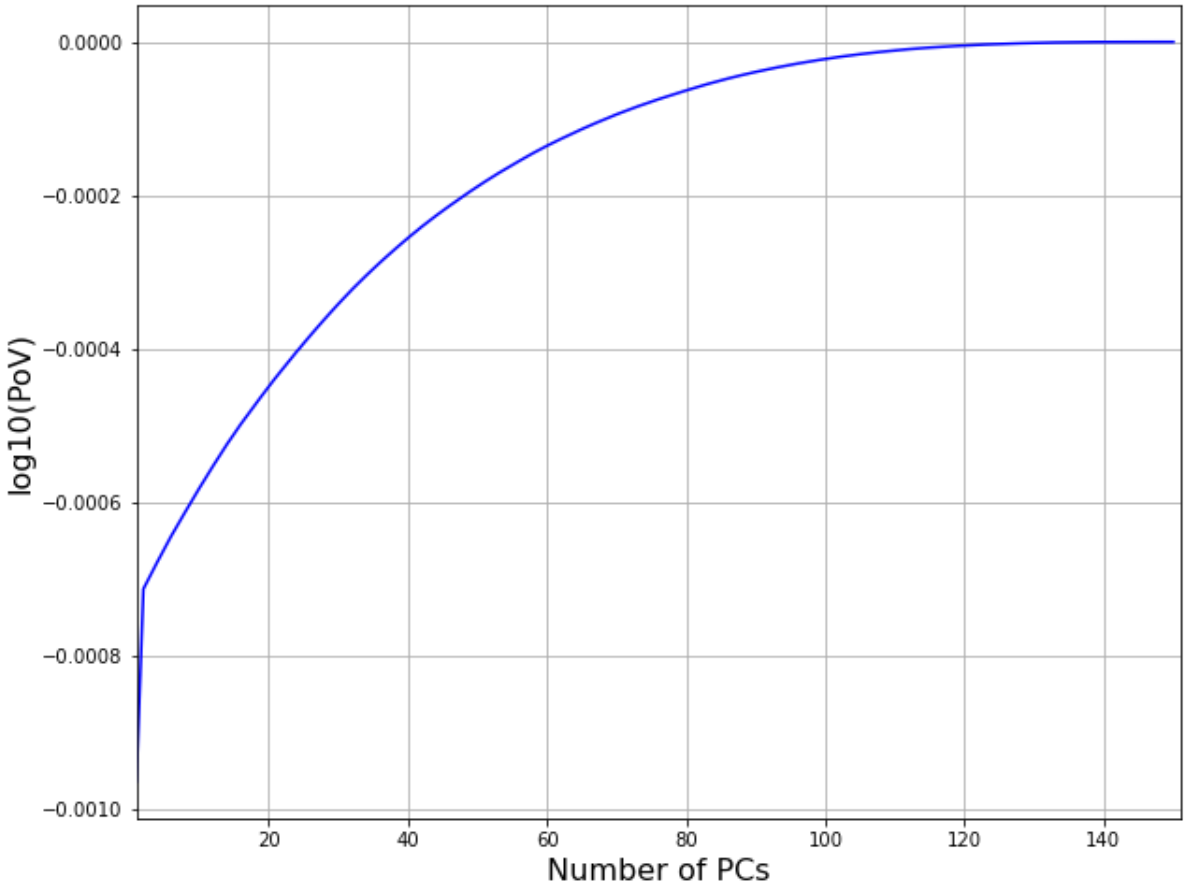

Run# 7 P0N#2 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

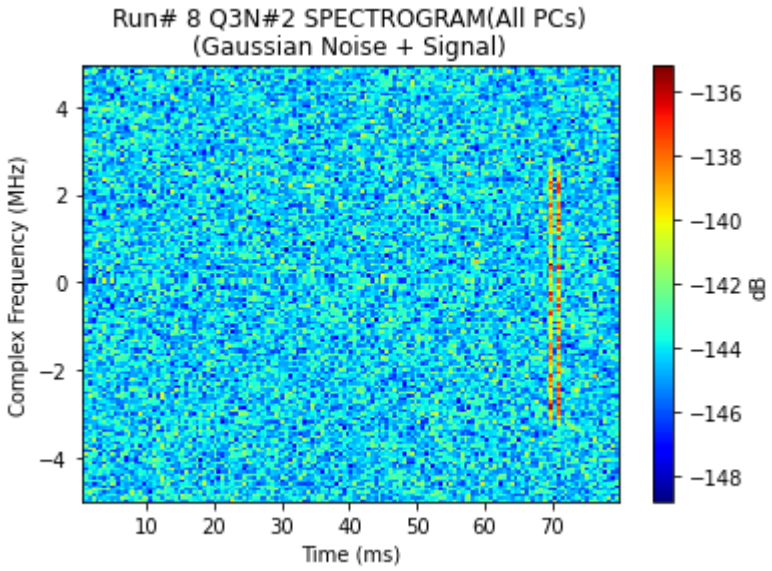

Run# 7 P0N#2 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

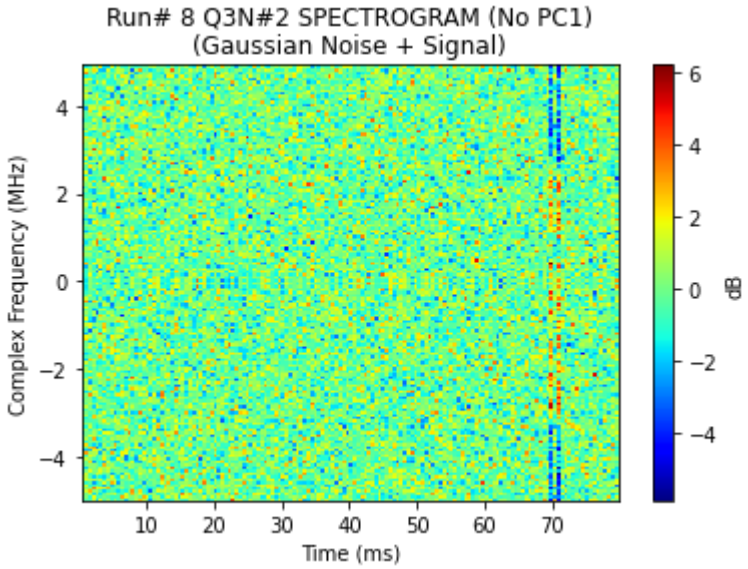

Run# 7 P0N#2 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

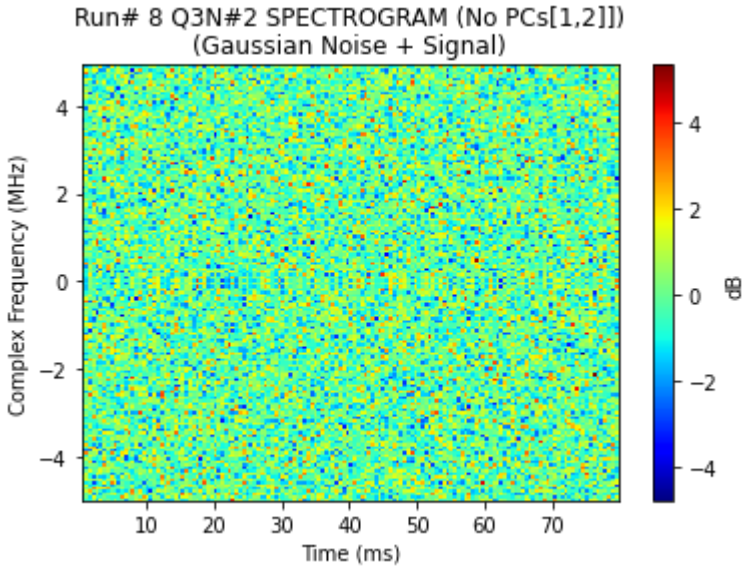

Run# 7 P0N#2 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

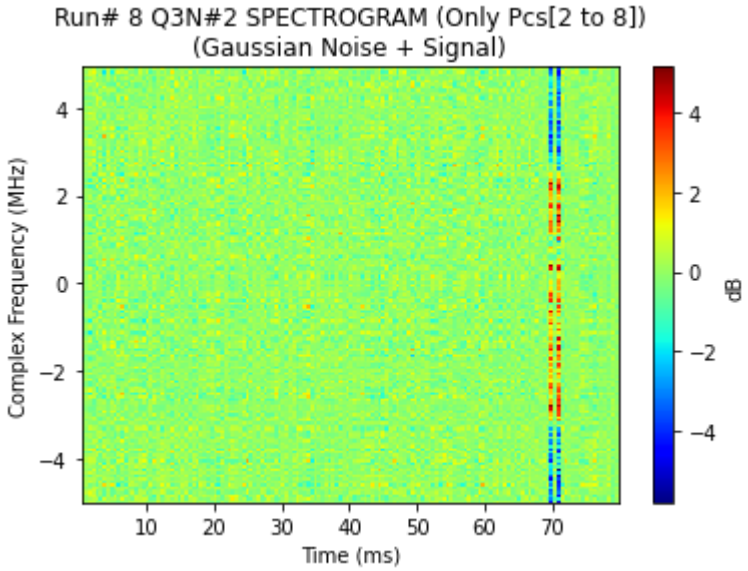

Run# 7 P0N#2 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

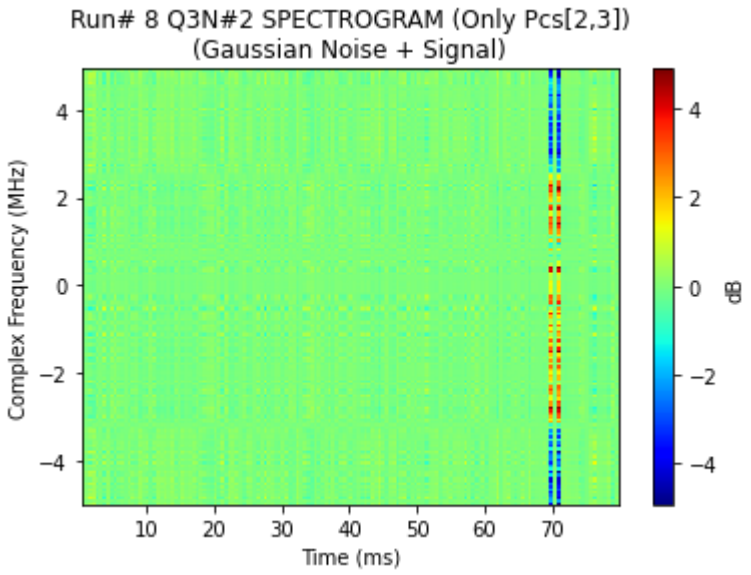

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

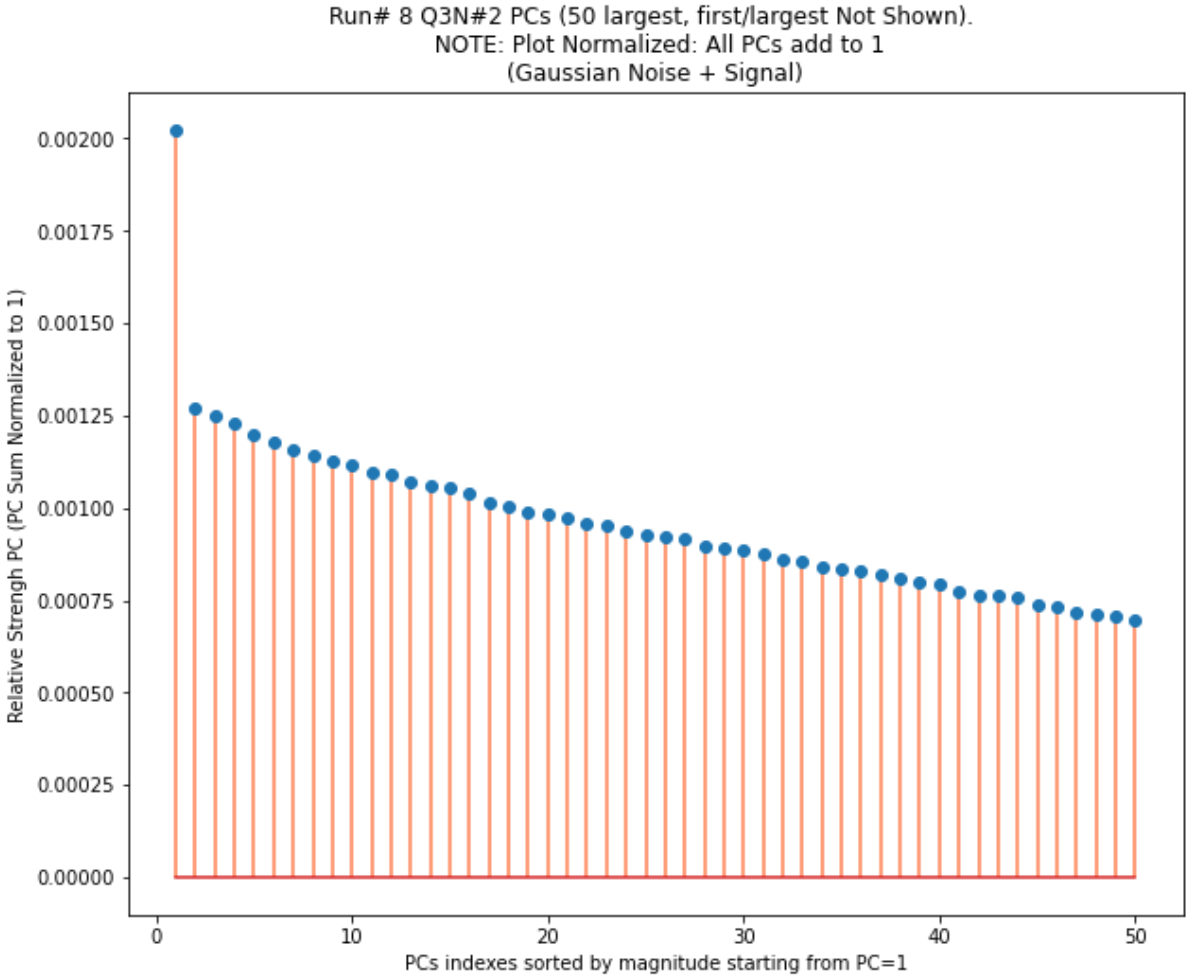

Run# 8 Q3N#2 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−136
−138
−140
−142
−144
−146
−148
dB

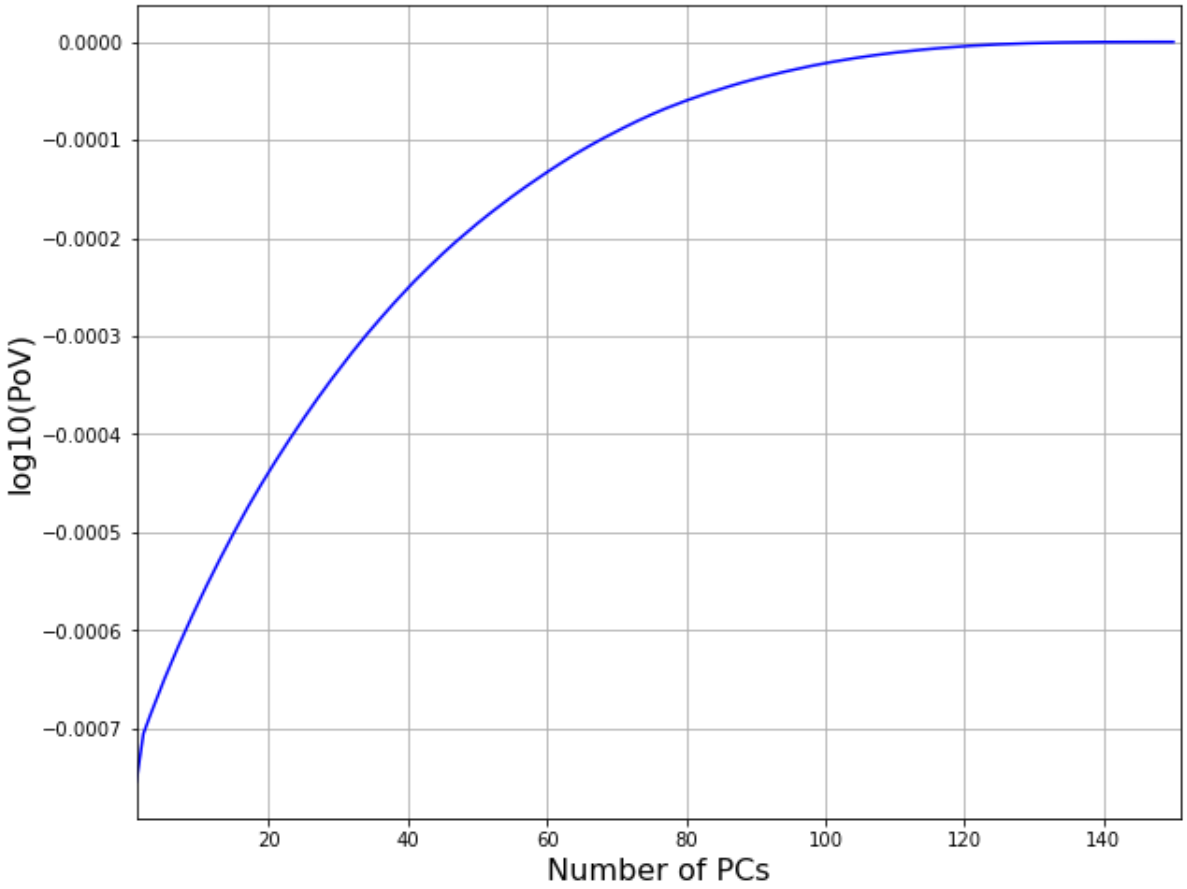

Run# 8 Q3N#2 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

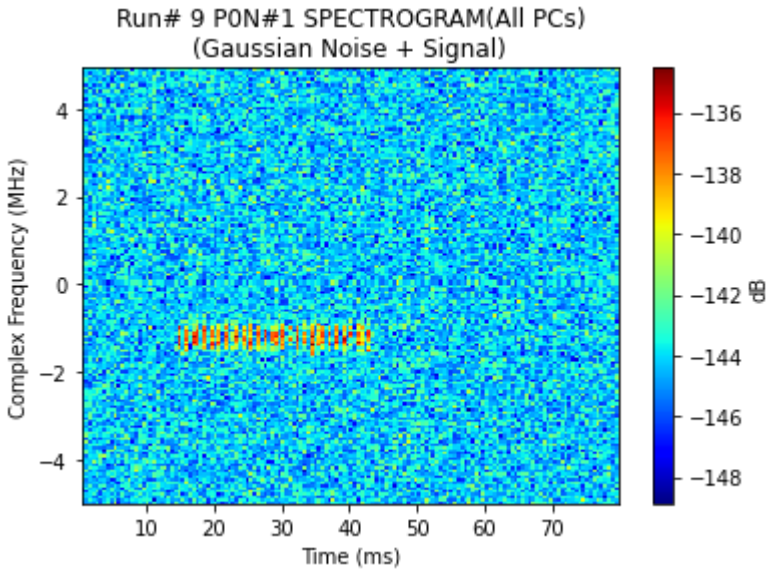

Run# 8 Q3N#2 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

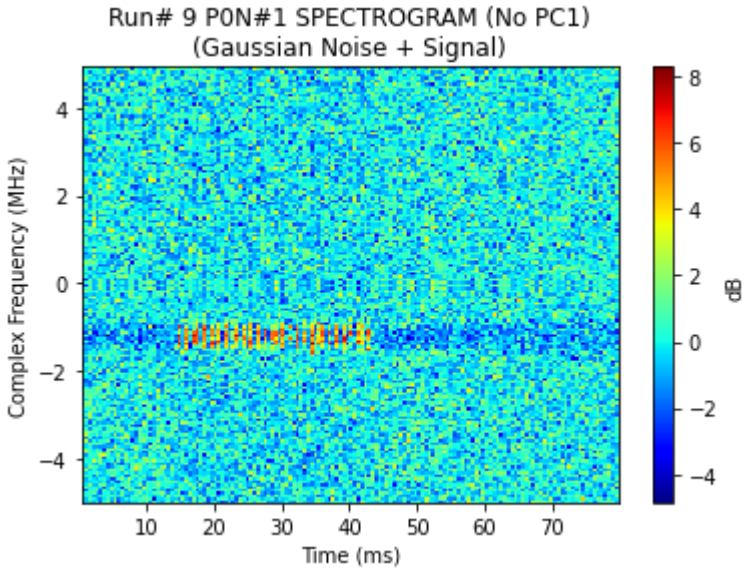

Run# 8 Q3N#2 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

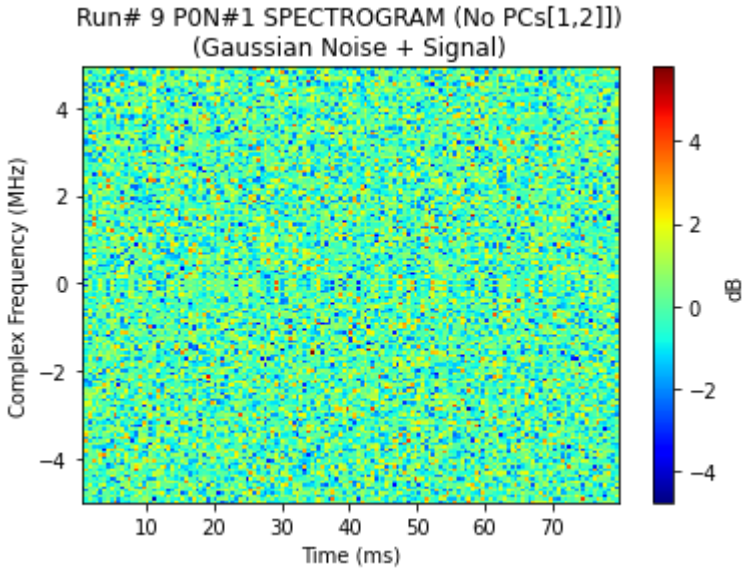

Run# 8 Q3N#2 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

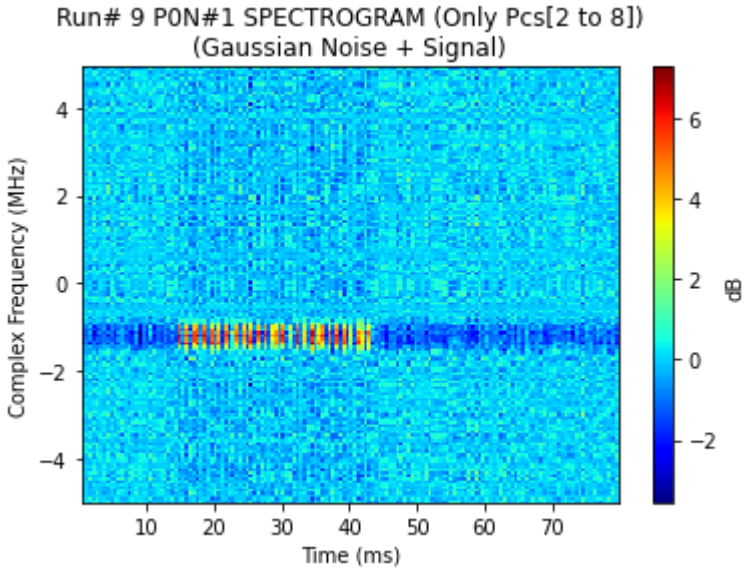

Run# 8 Q3N#2 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

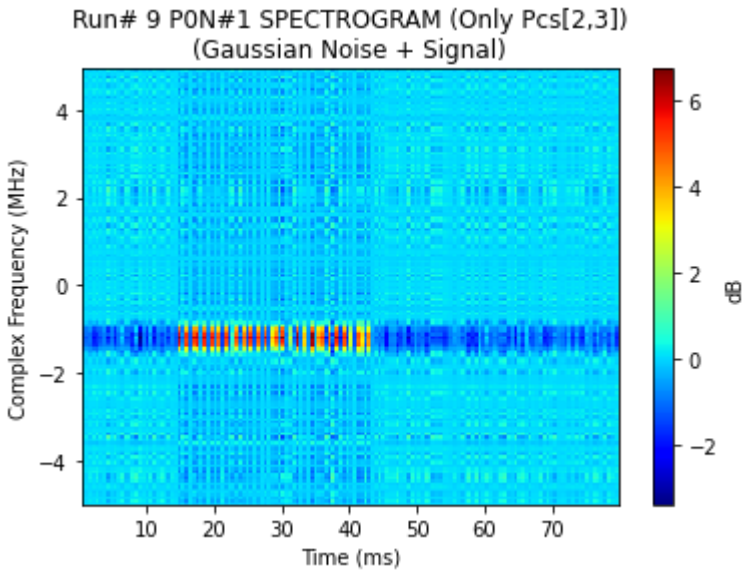

0.0000
−0.0001
−0.0002
−0.0003
−0.0004
−0.0005
−0.0006
−0.0007
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

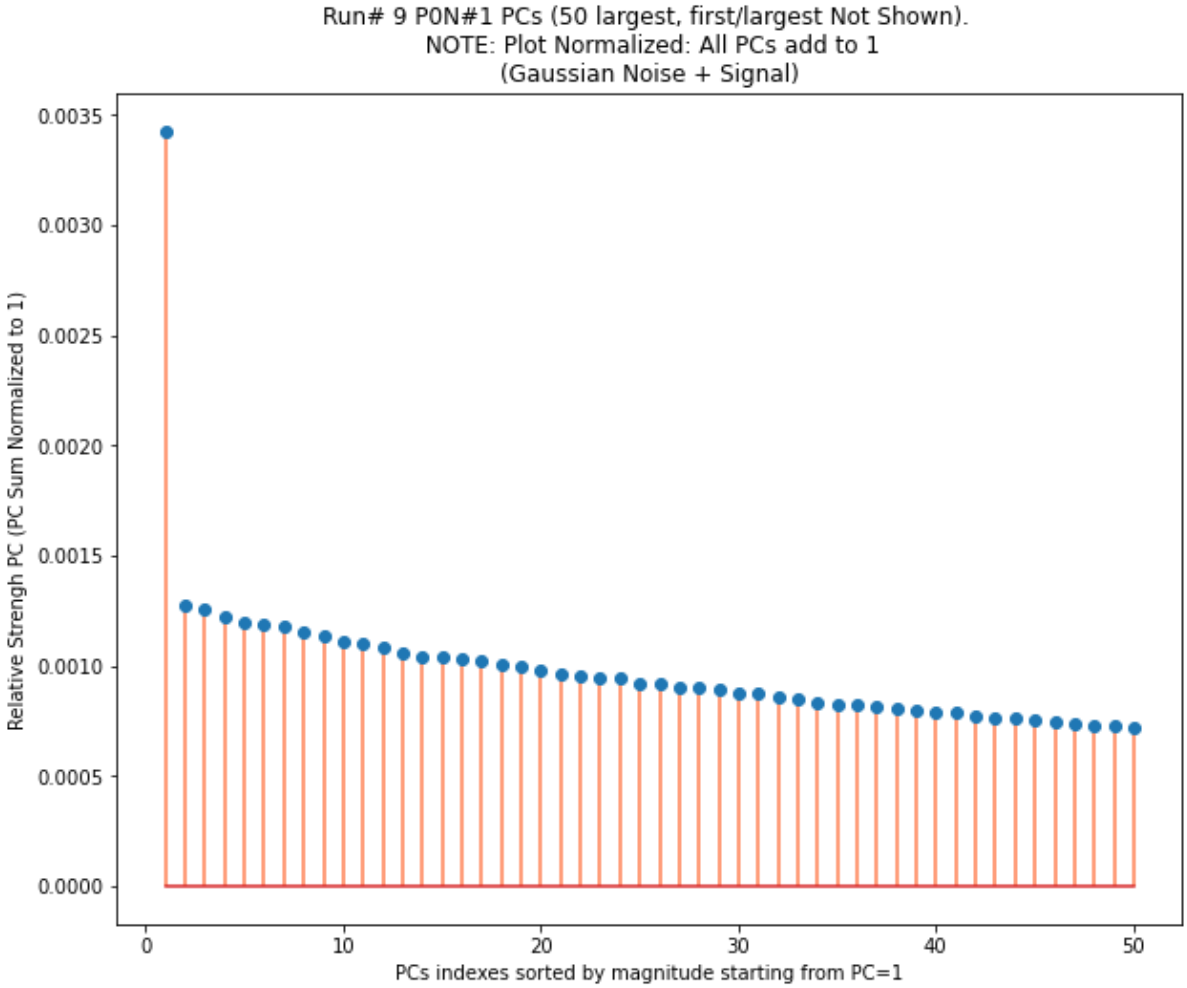

Run# 9 P0N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−136
−138
−140
−142
−144
−146
−148
dB

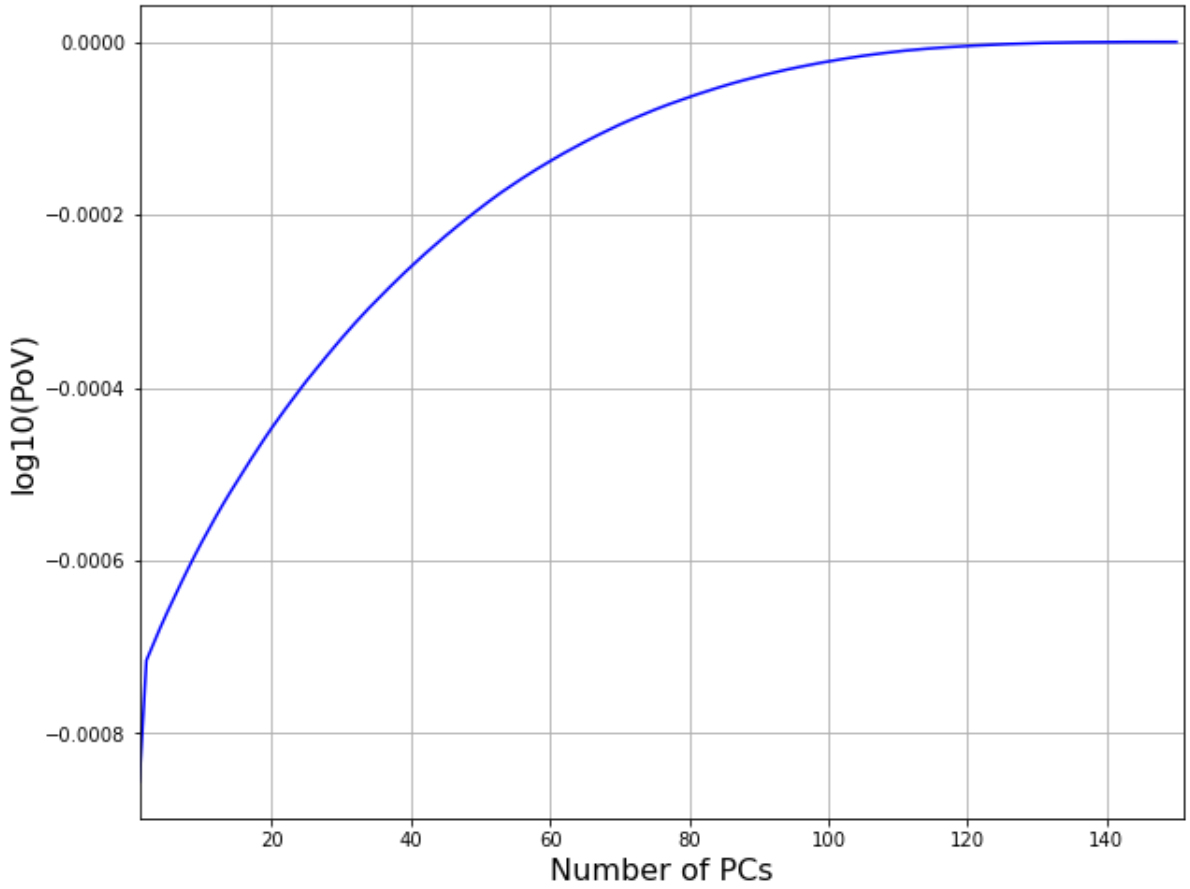

Run# 9 P0N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

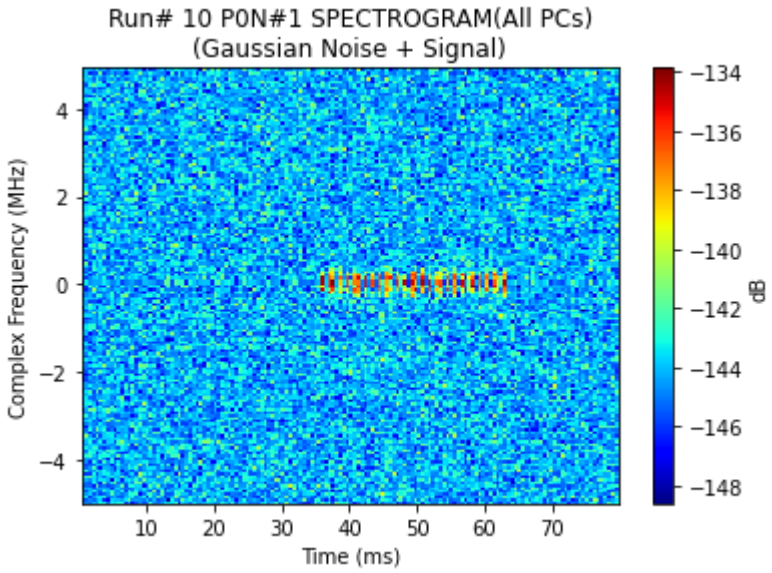

Run# 9 P0N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

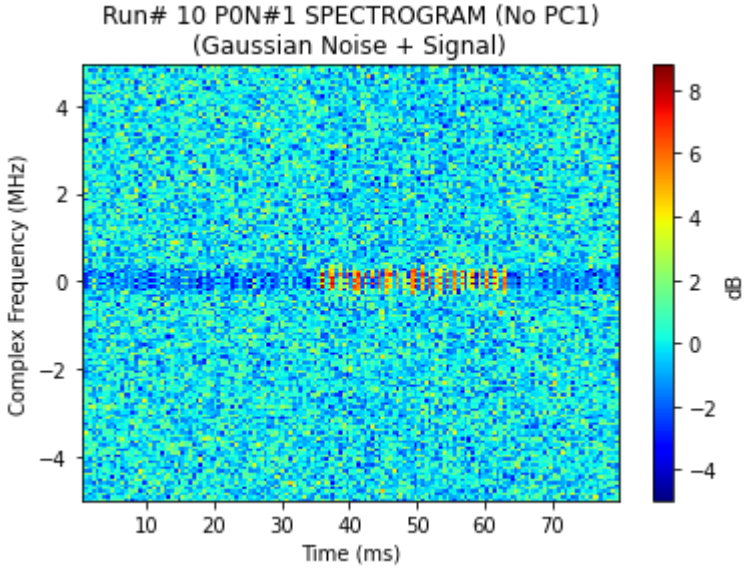

Run# 9 P0N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

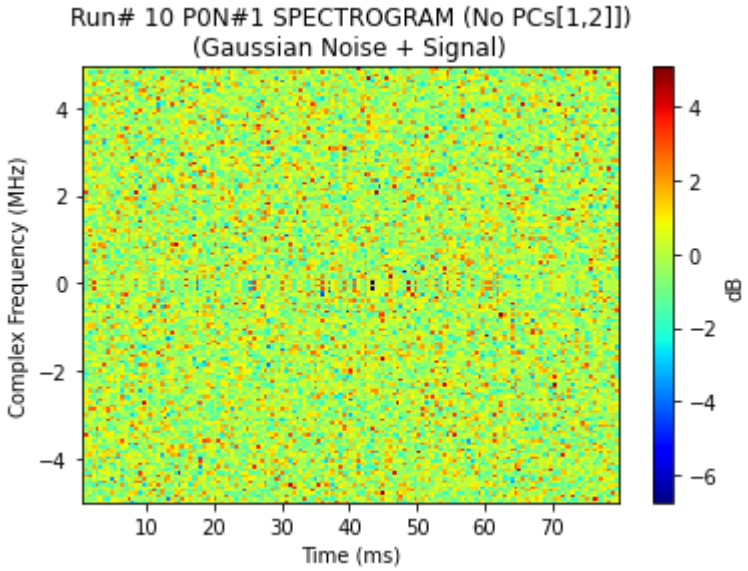

Run# 9 P0N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

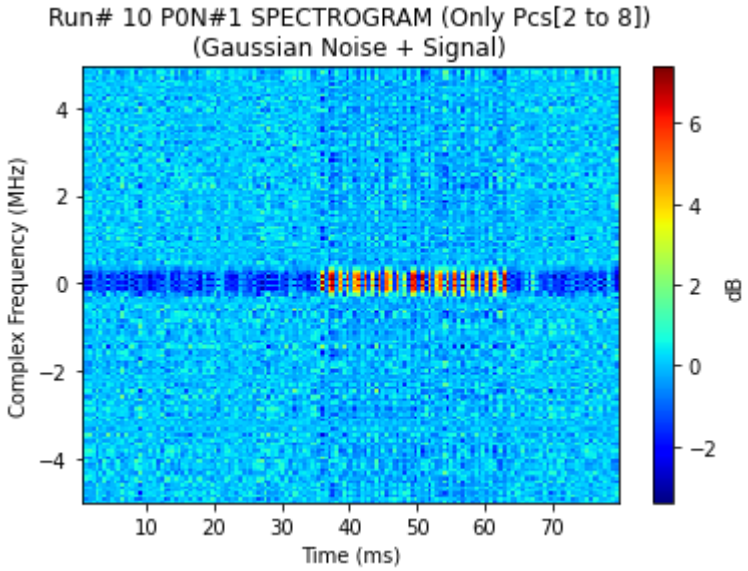

Run# 9 P0N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

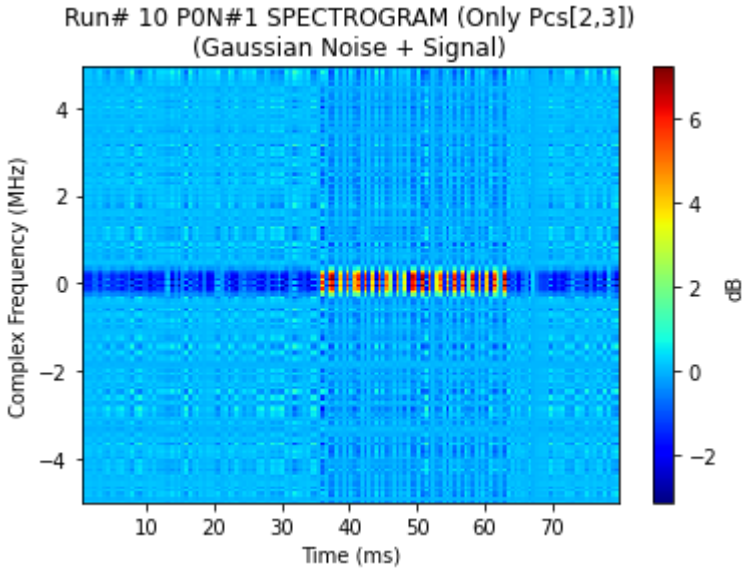

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

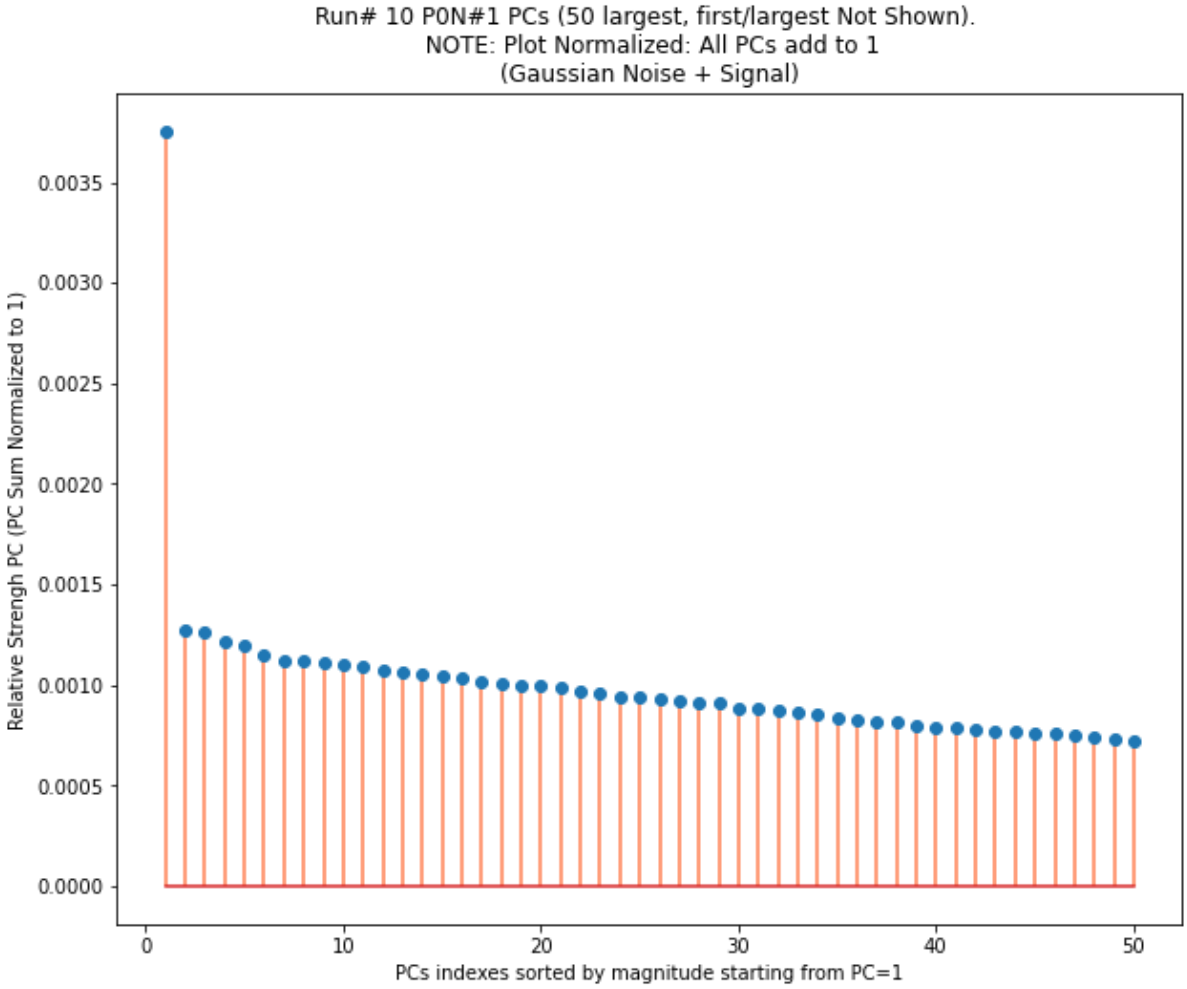

Run# 10 P0N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−134
−136
−138
−140
−142
−144
−146
−148
dB

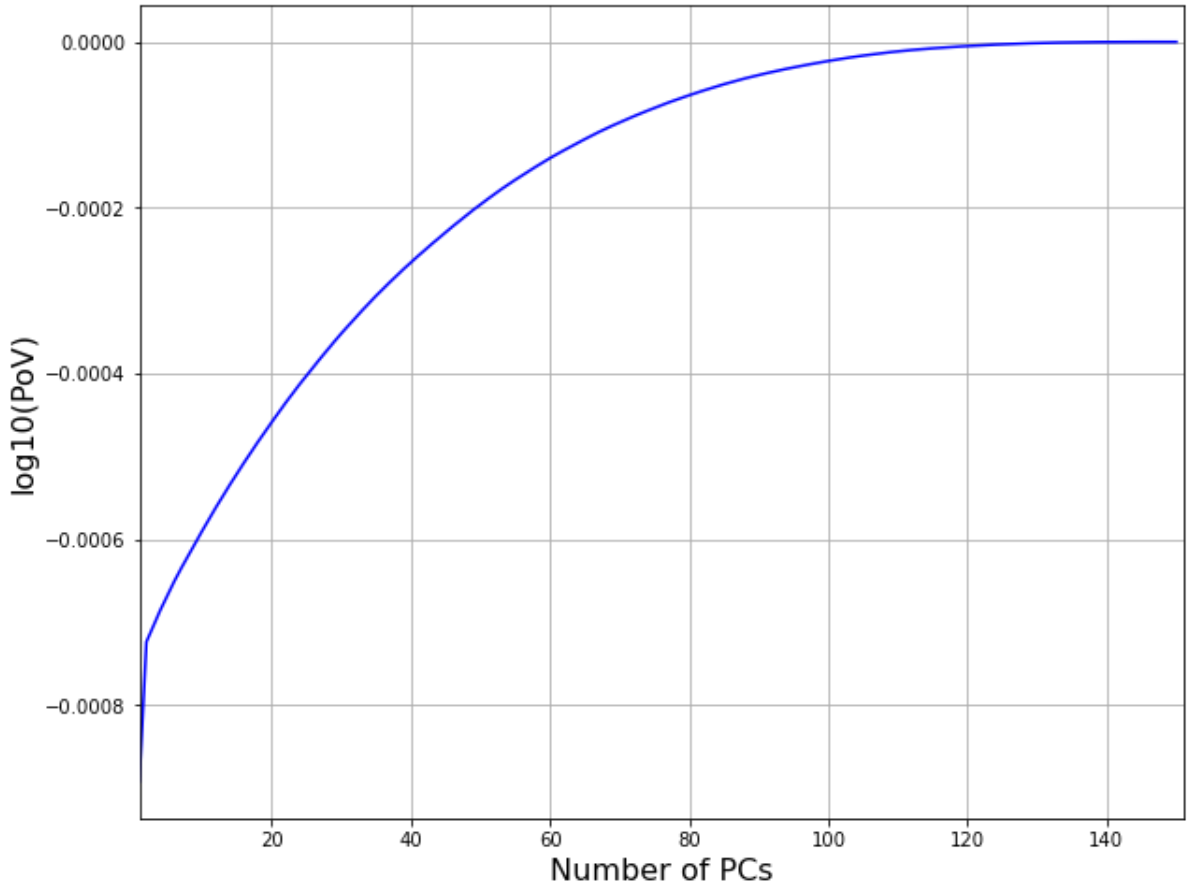

Run# 10 P0N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

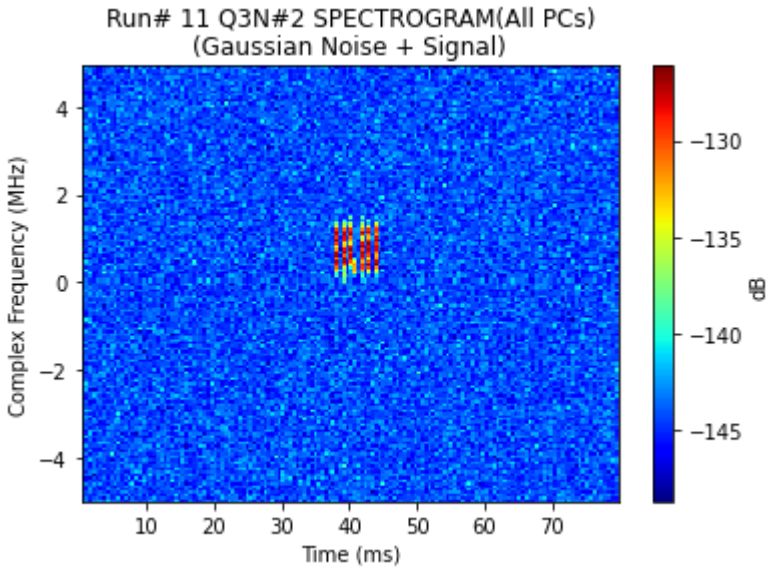

Run# 10 P0N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

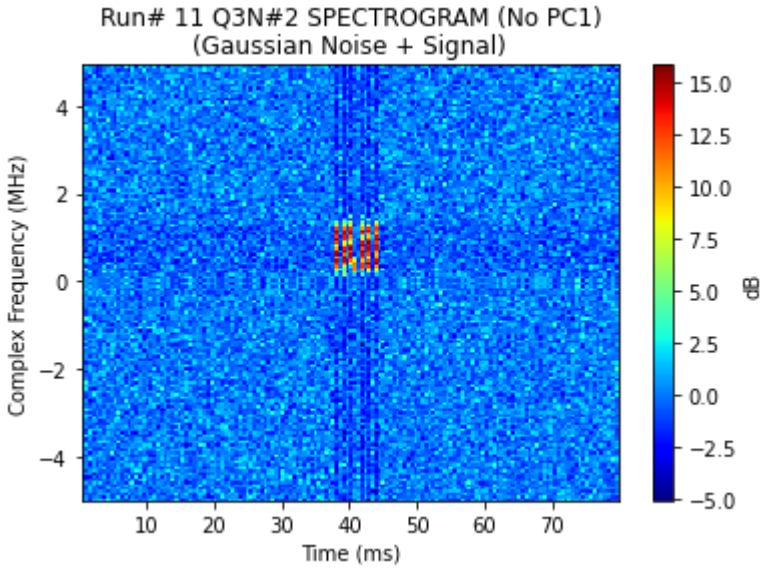

Run# 10 P0N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

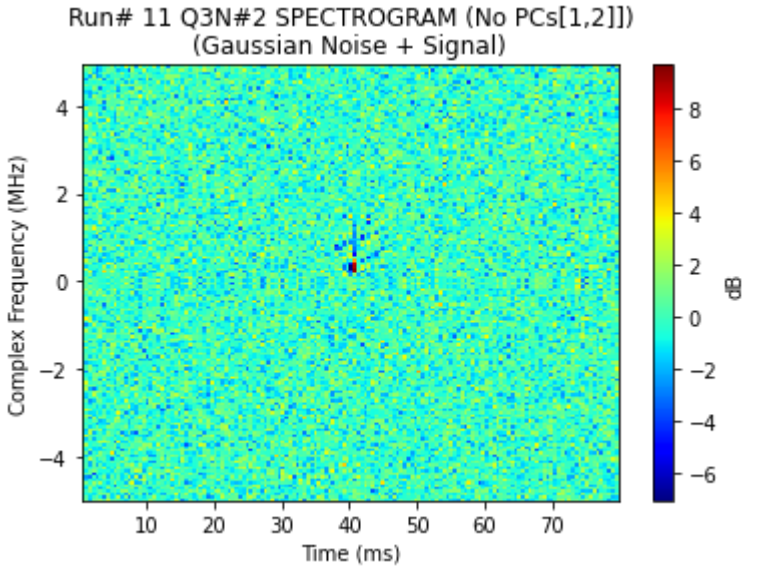

Run# 10 P0N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

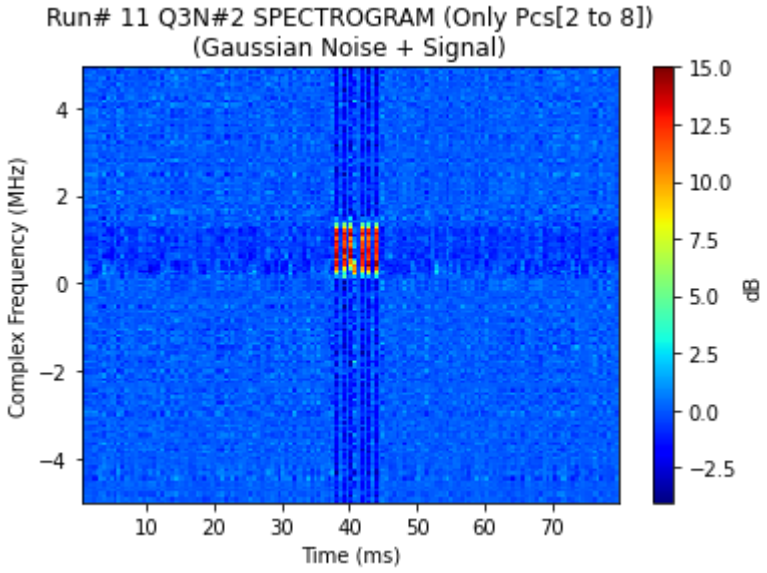

Run# 10 P0N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

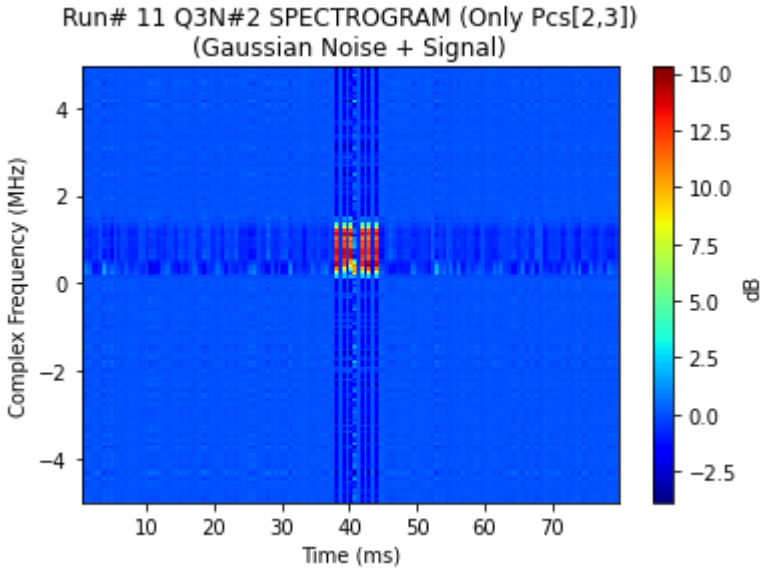

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

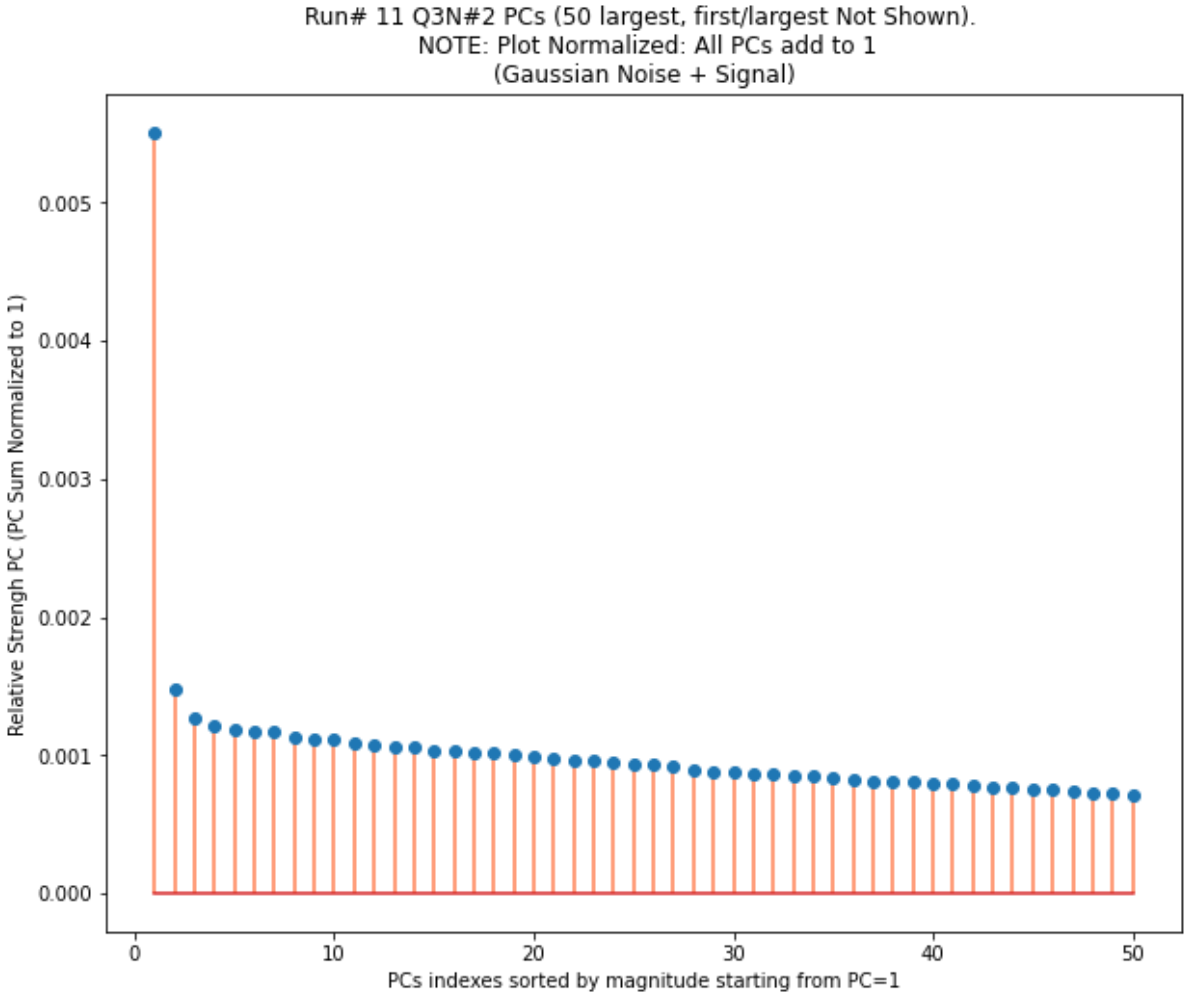

Run# 11 Q3N#2 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−130
−135
−140
−145
dB

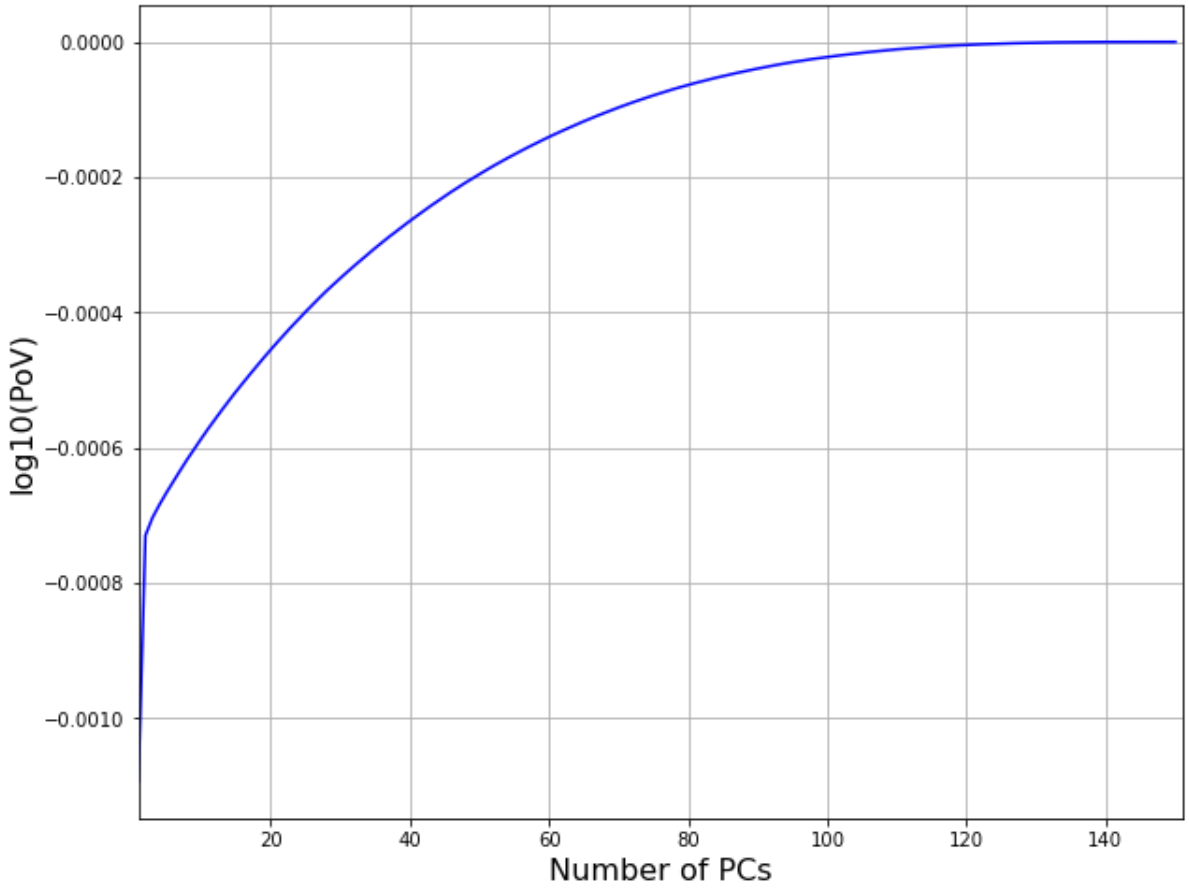

Run# 11 Q3N#2 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

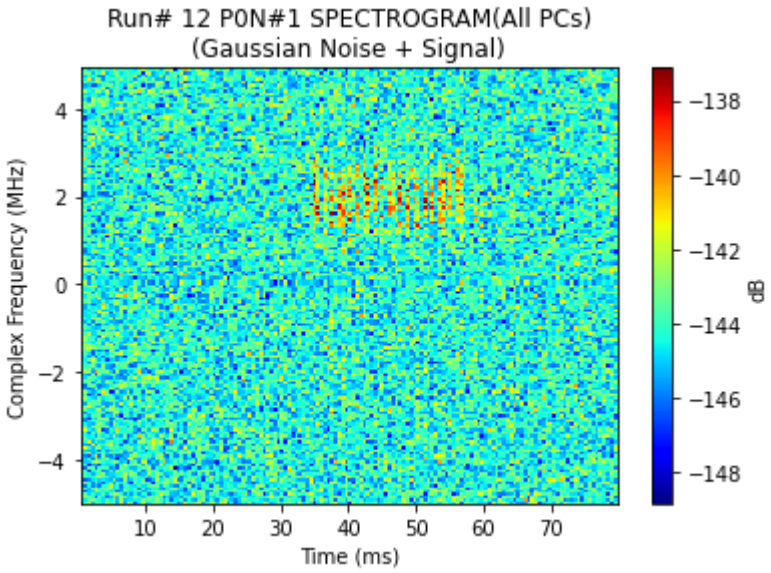

Run# 11 Q3N#2 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

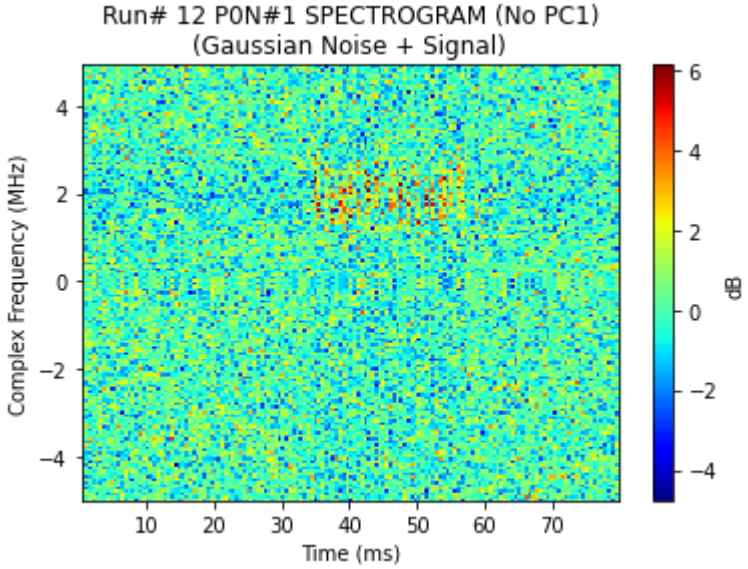

Run# 11 Q3N#2 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

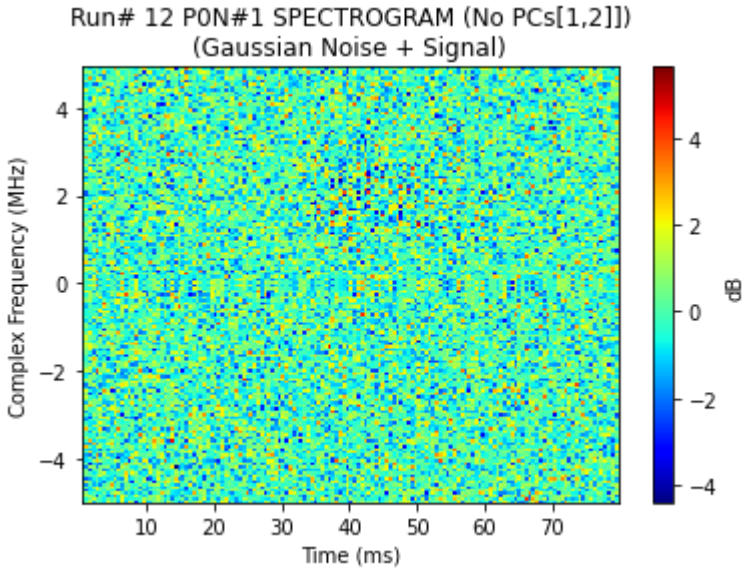

Run# 11 Q3N#2 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB
4
2
0
−2
−4
10
20
30
40
50
60
70
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−2.5

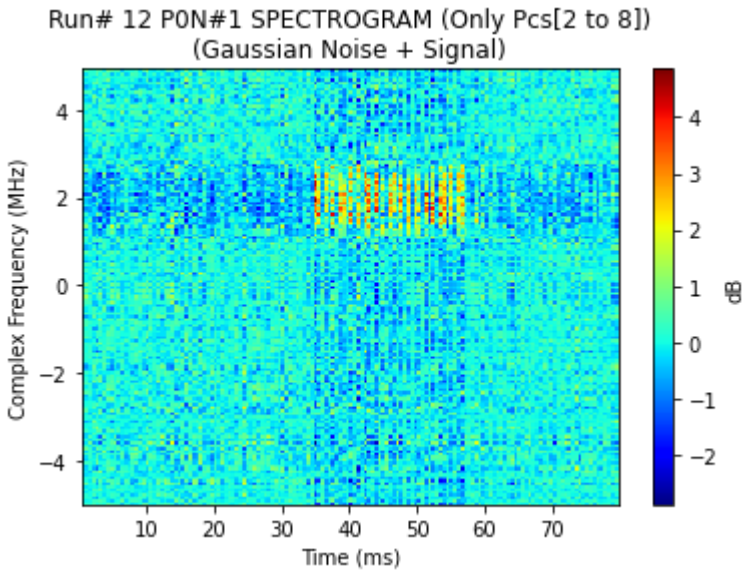

Run# 11 Q3N#2 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1
0.005
0.004
0.003
0.002
0.001
0.000
0
10
20
30
40
50

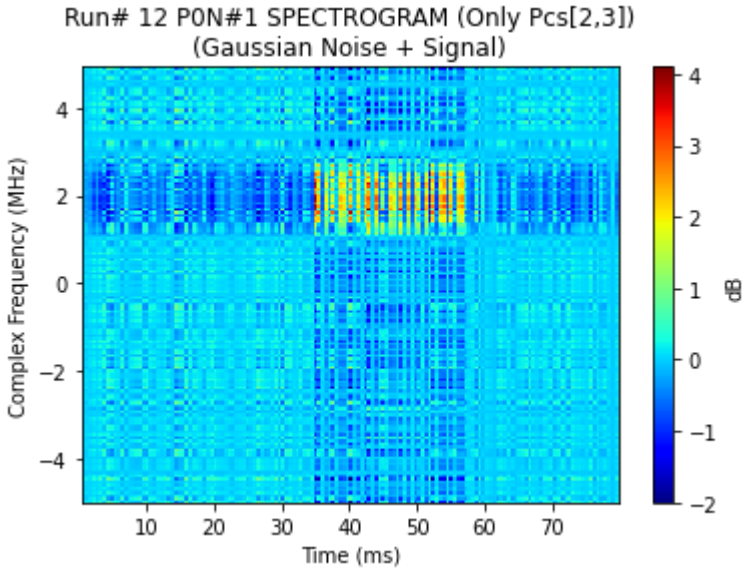

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

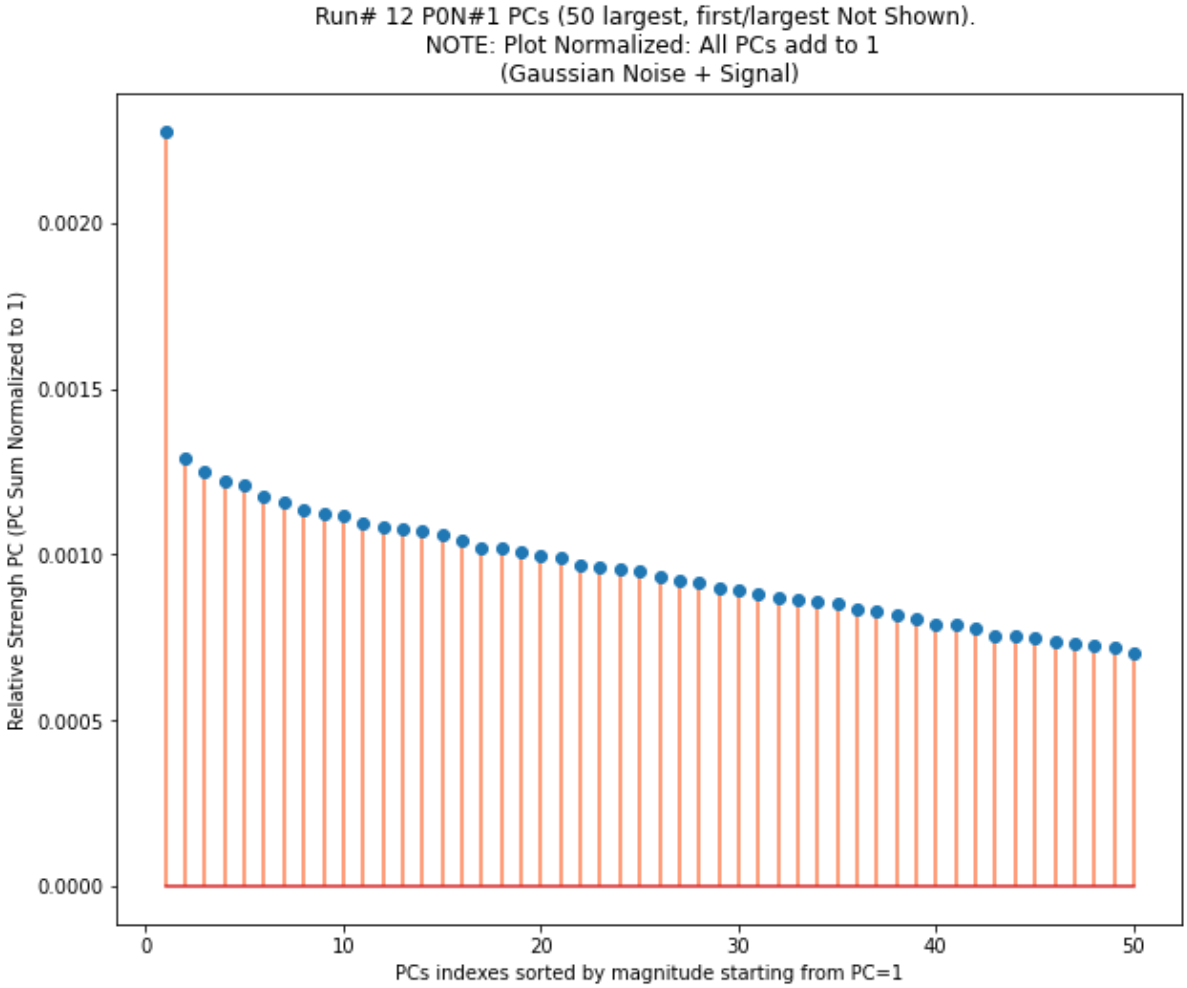

Run# 12 P0N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−138
−140
−142
−144
−146
−148
dB

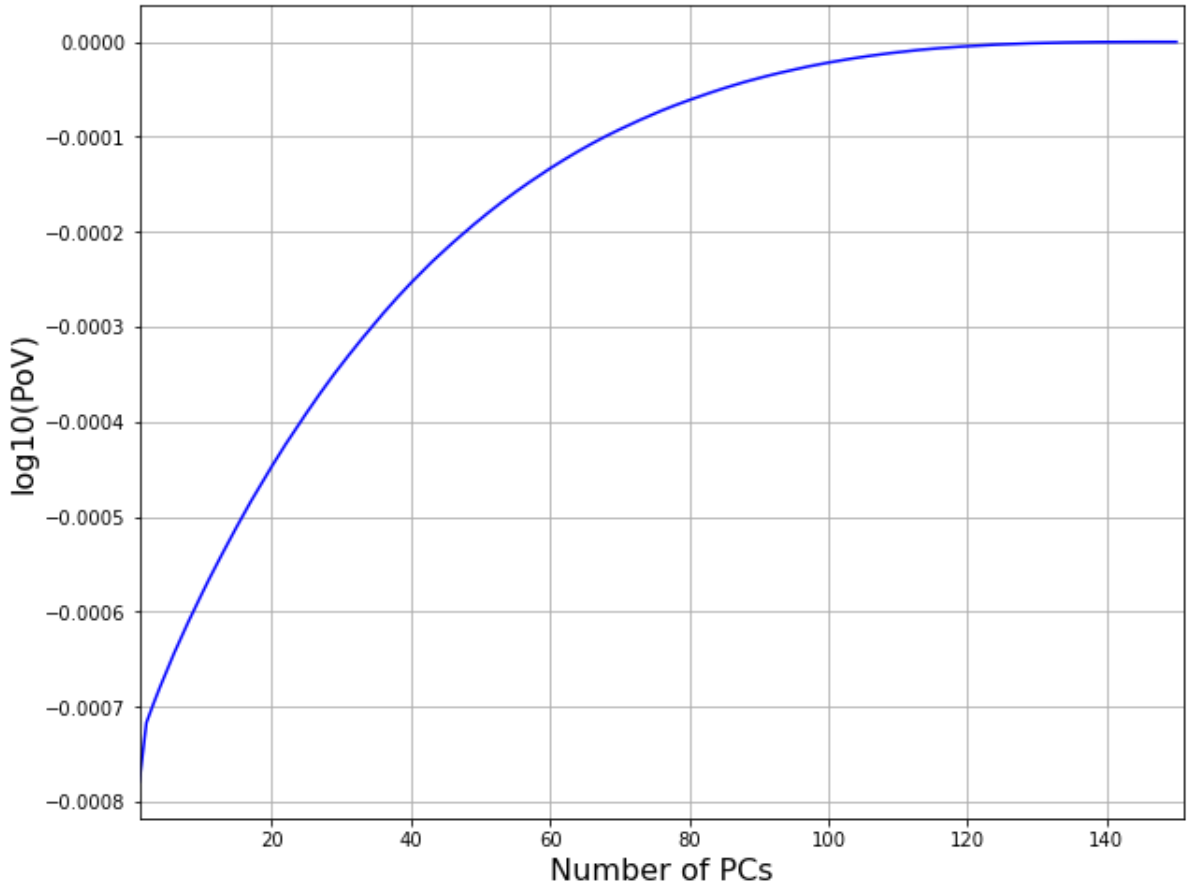

Run# 12 P0N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

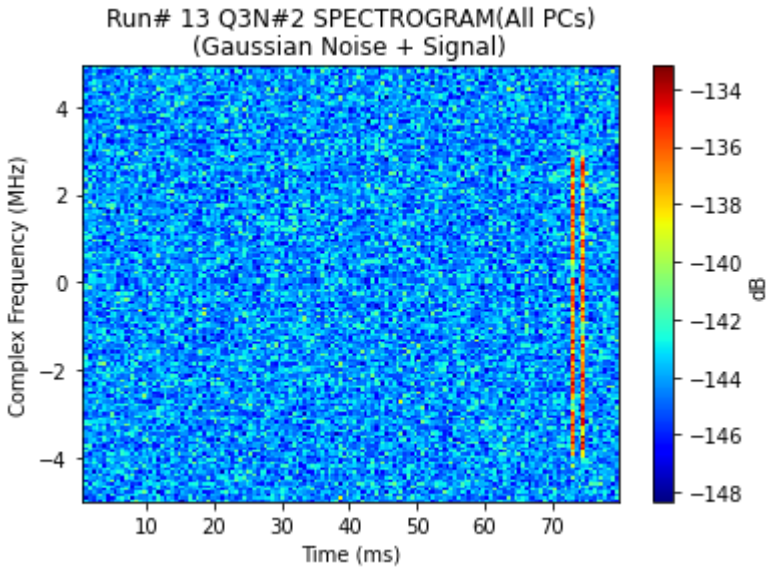

Run# 12 P0N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

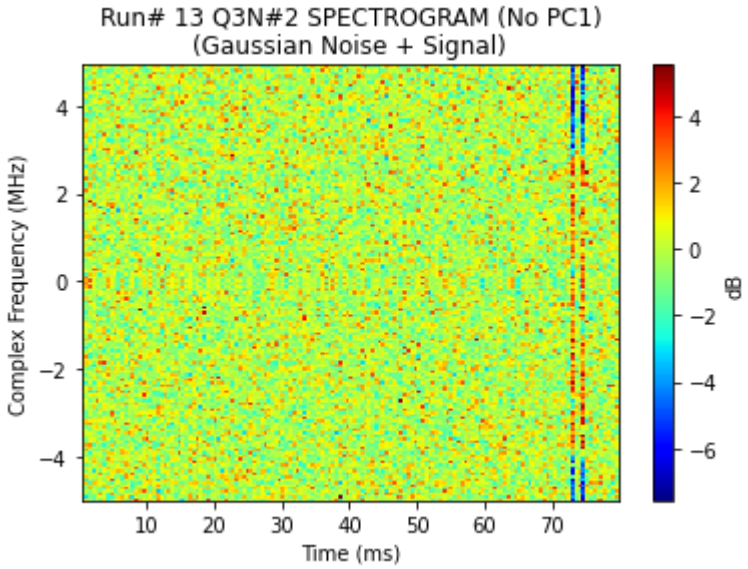

Run# 12 P0N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

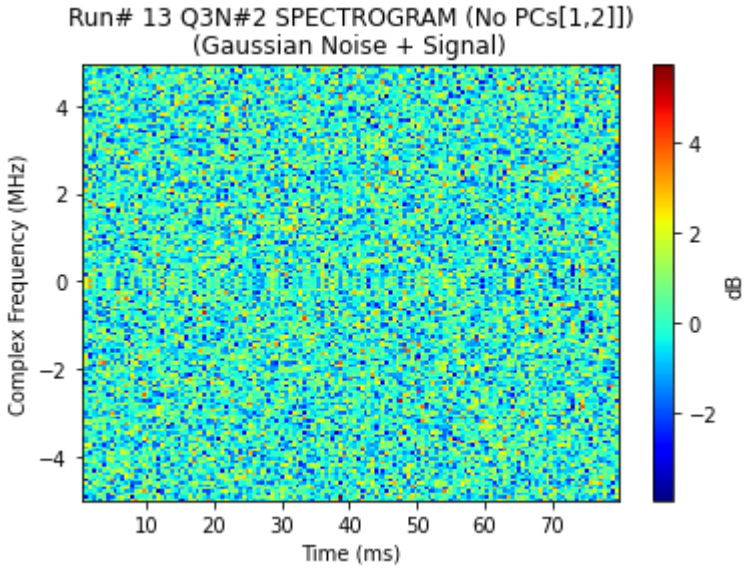

Run# 12 P0N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

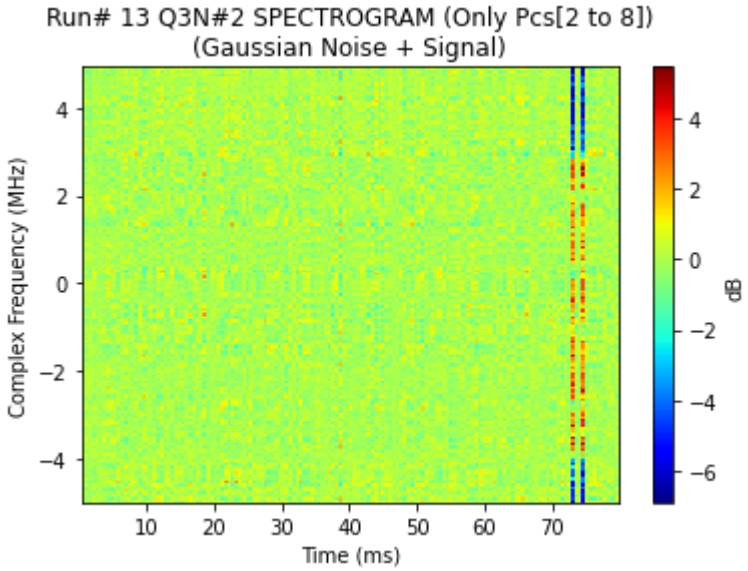

Run# 12 P0N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

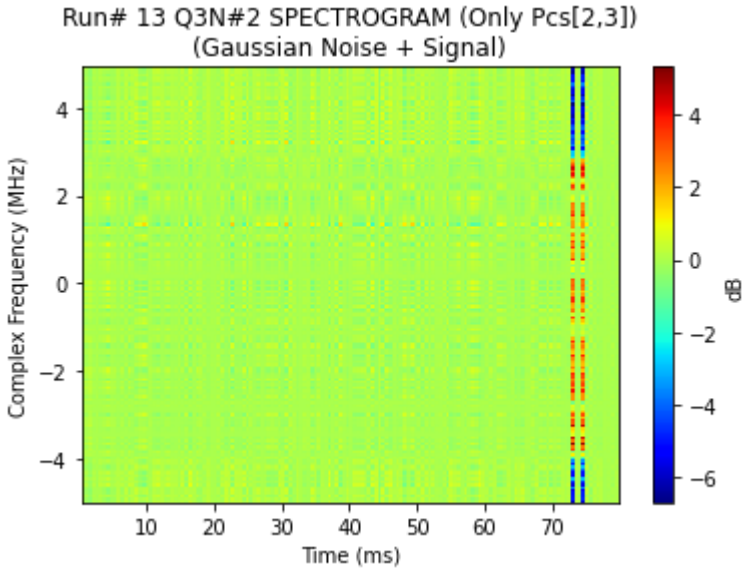

log10(PoV)
Number of PCs
0.0000
−0.0001
−0.0002
−0.0003
−0.0004
−0.0005
−0.0006
−0.0007
−0.0008
20
40
60
80
100
120
140

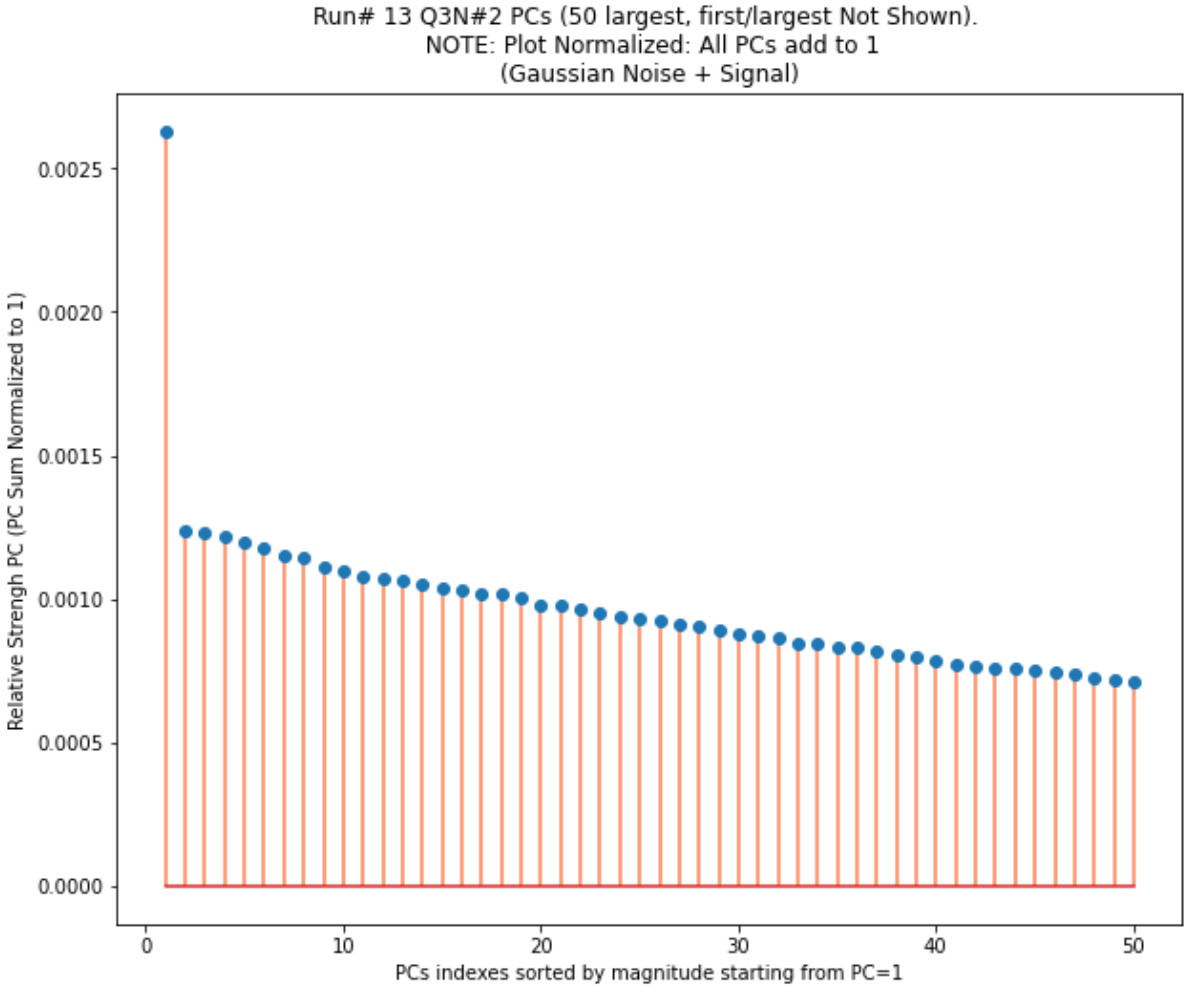

Run# 13 Q3N#2 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB
4
2
0
−2
−4
10
20
30
40
50
60
70
−134
−136
−138
−140
−142
−144
−146
−148

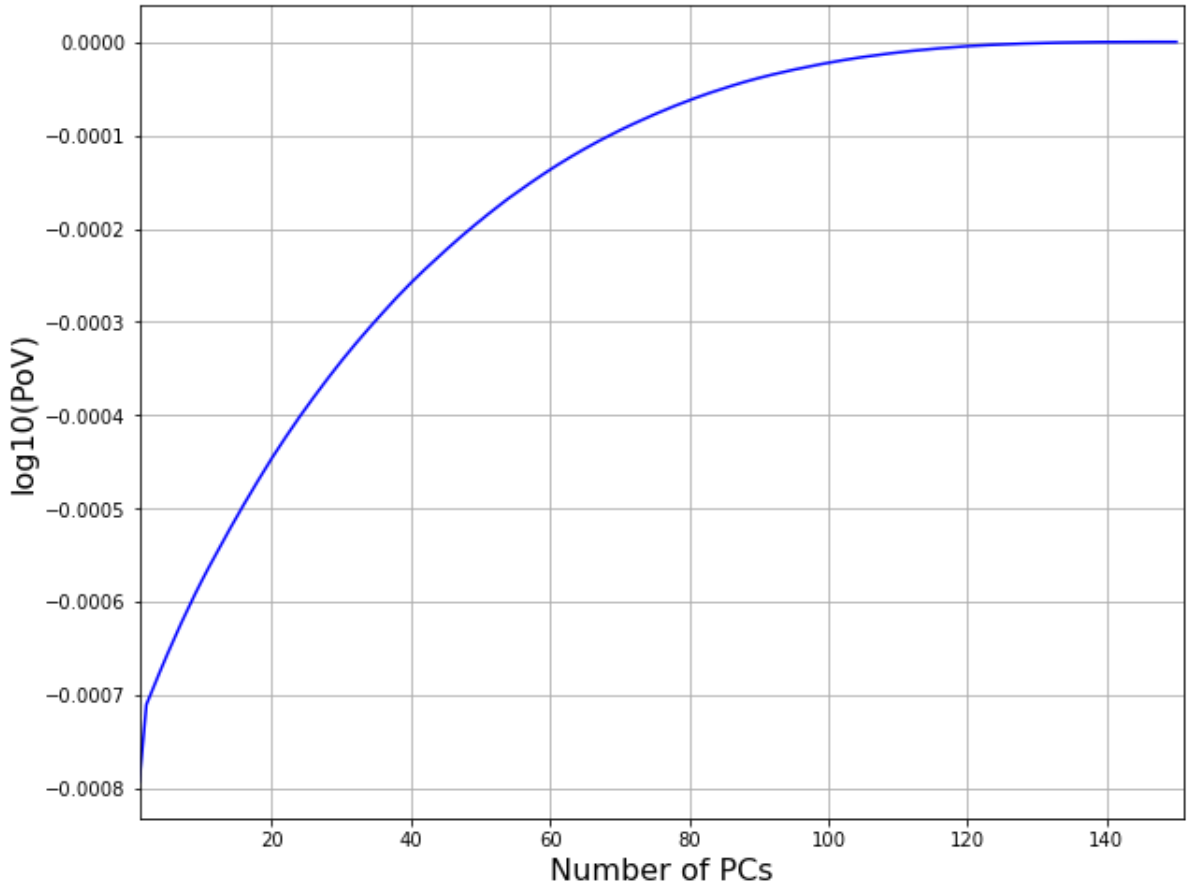

Run# 13 Q3N#2 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

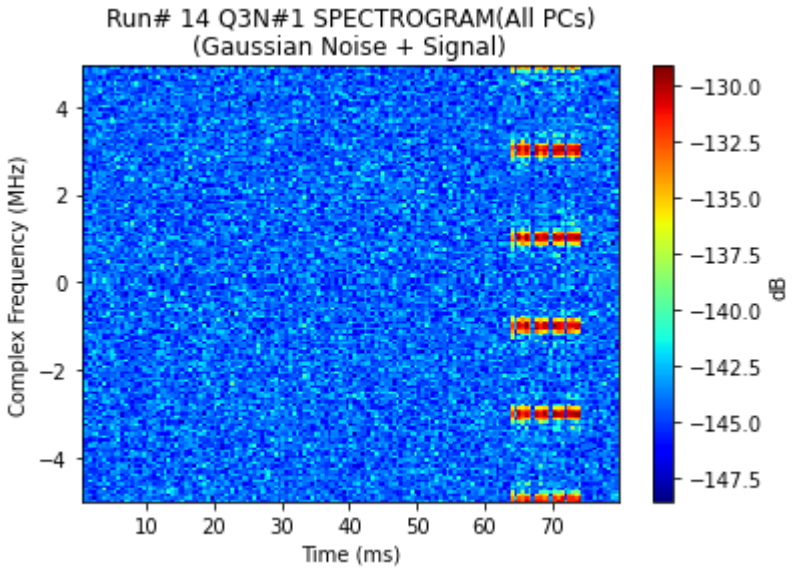

Run# 13 Q3N#2 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

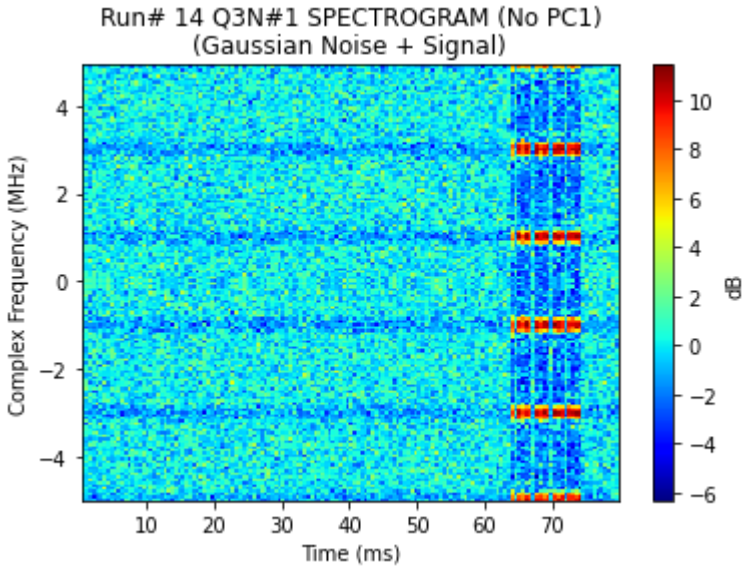

Run# 13 Q3N#2 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

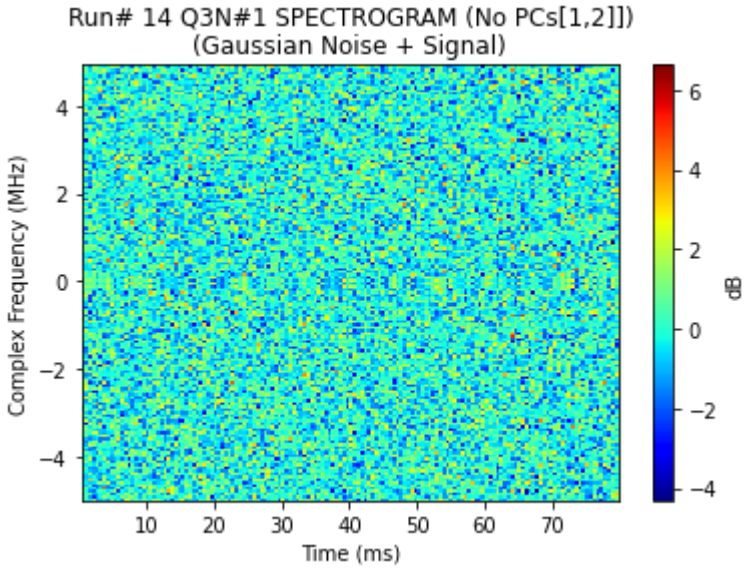

Run# 13 Q3N#2 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

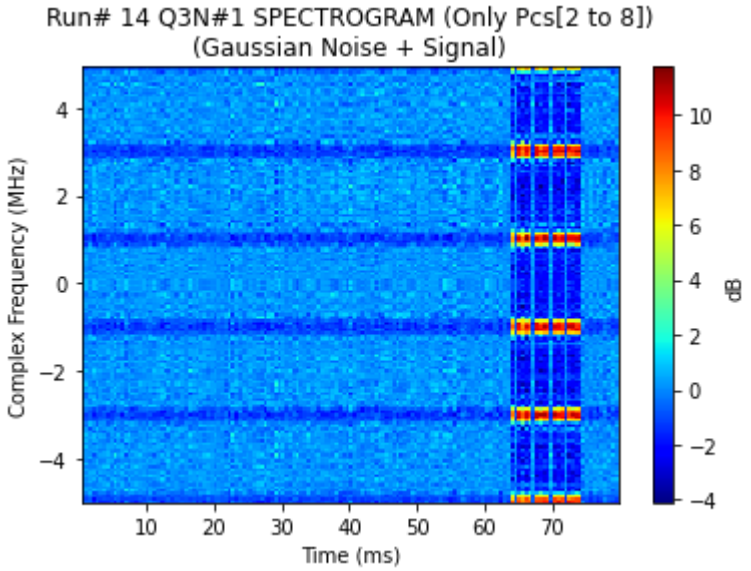

Run# 13 Q3N#2 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

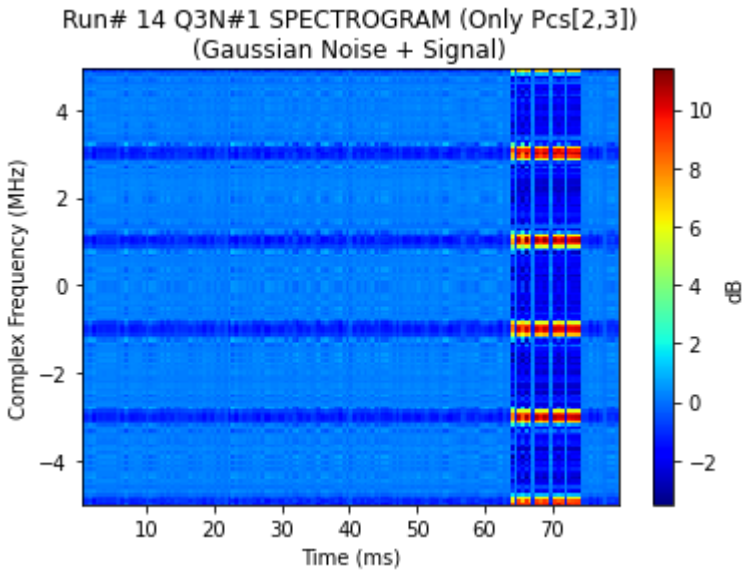

0.0000
−0.0001
−0.0002
−0.0003
−0.0004
−0.0005
−0.0006
−0.0007
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

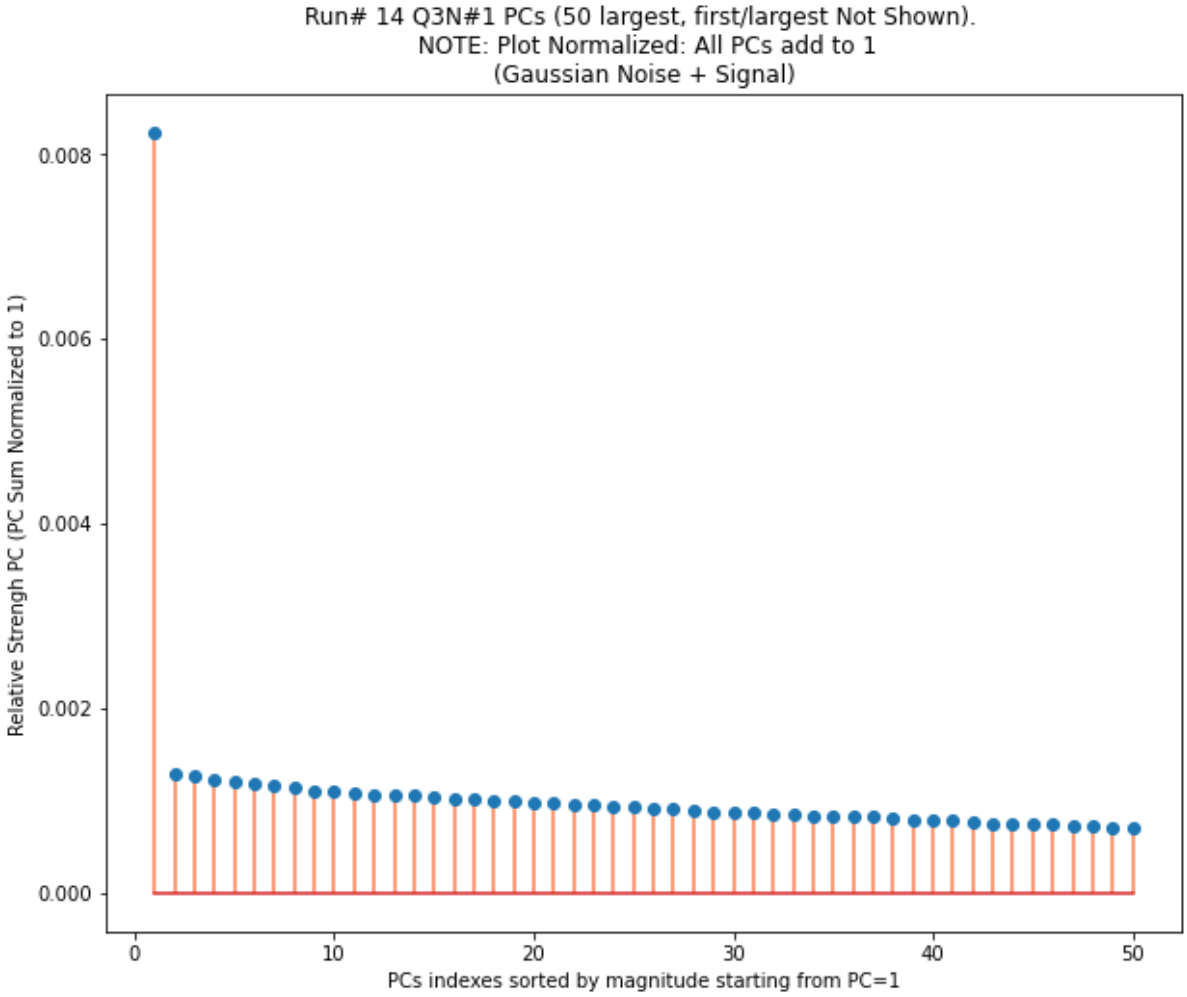

Run# 14 Q3N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−130.0
−132.5
−135.0
−137.5
−140.0
−142.5
−145.0
−147.5
dB

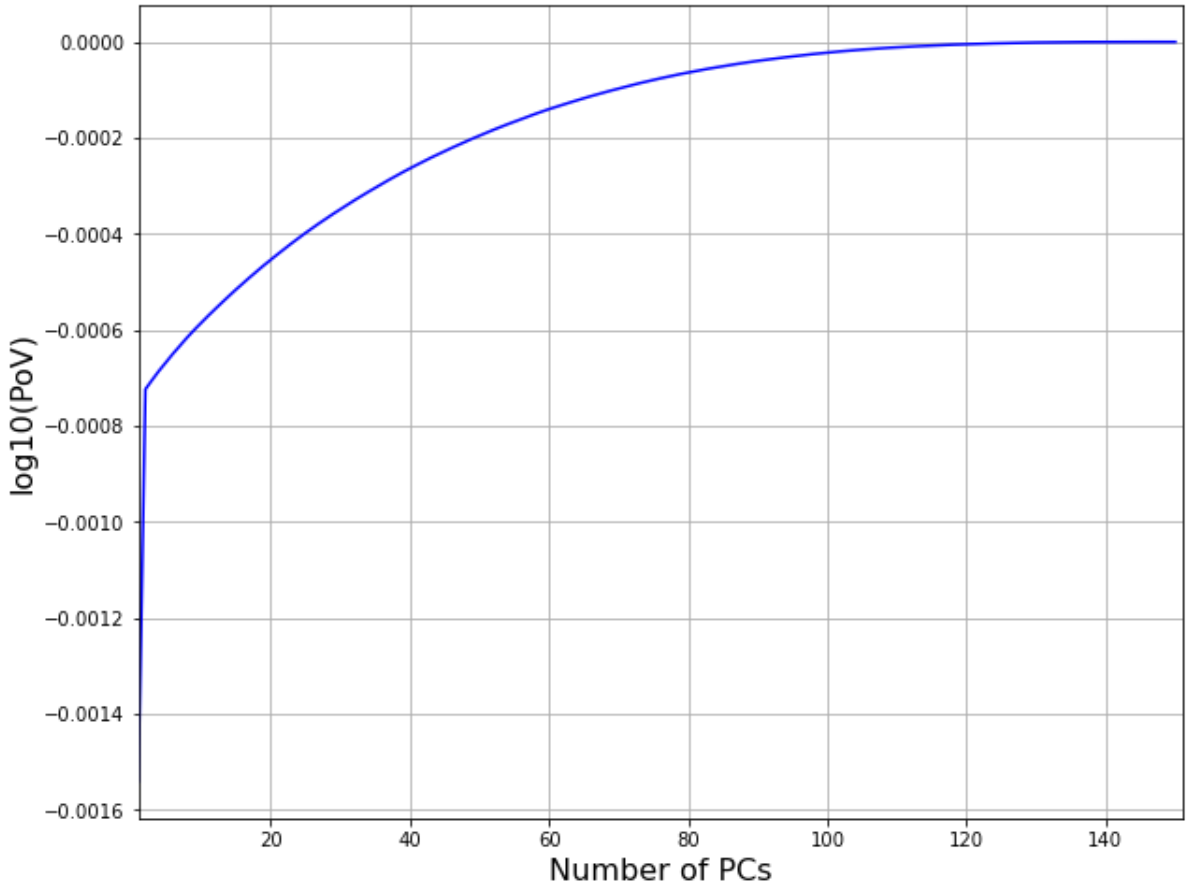

Run# 14 Q3N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

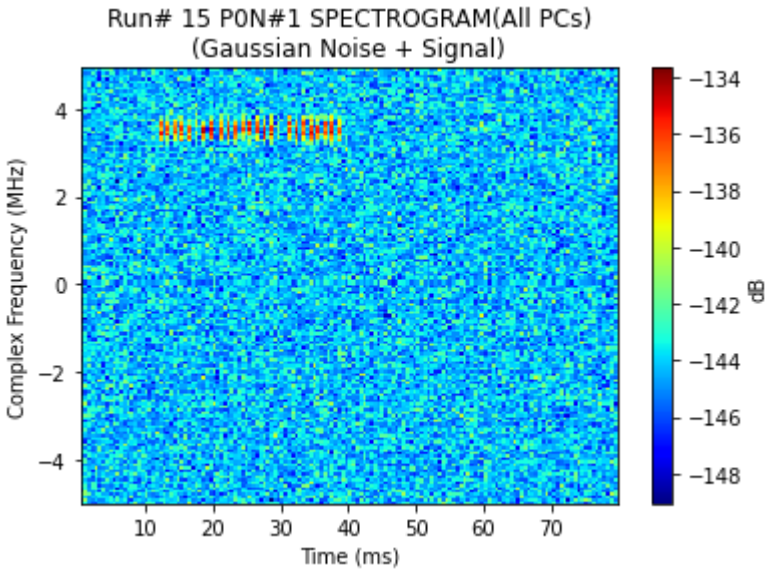

Run# 14 Q3N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

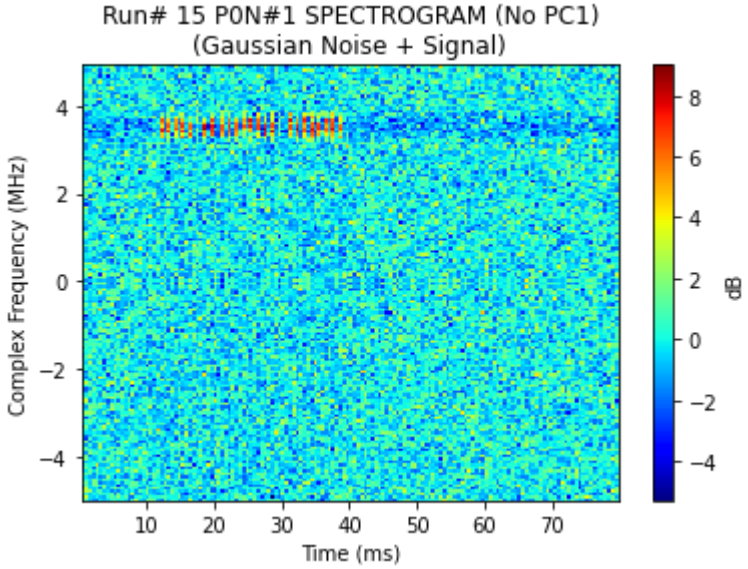

Run# 14 Q3N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

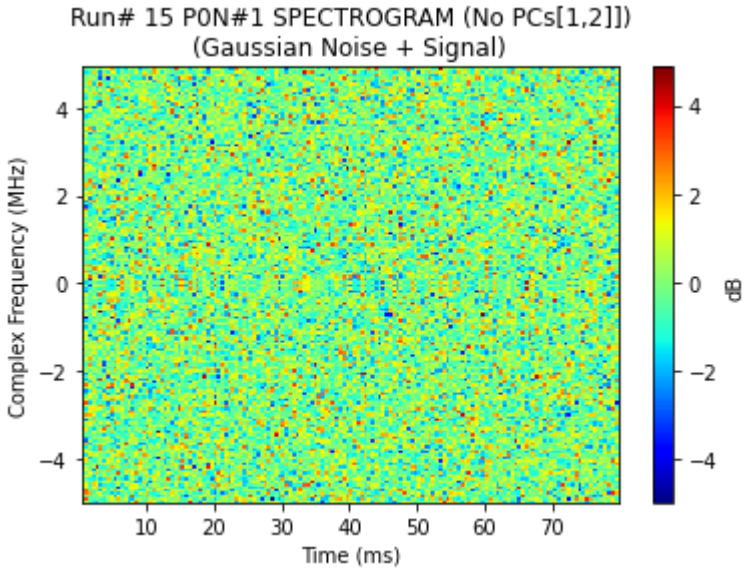

Run# 14 Q3N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

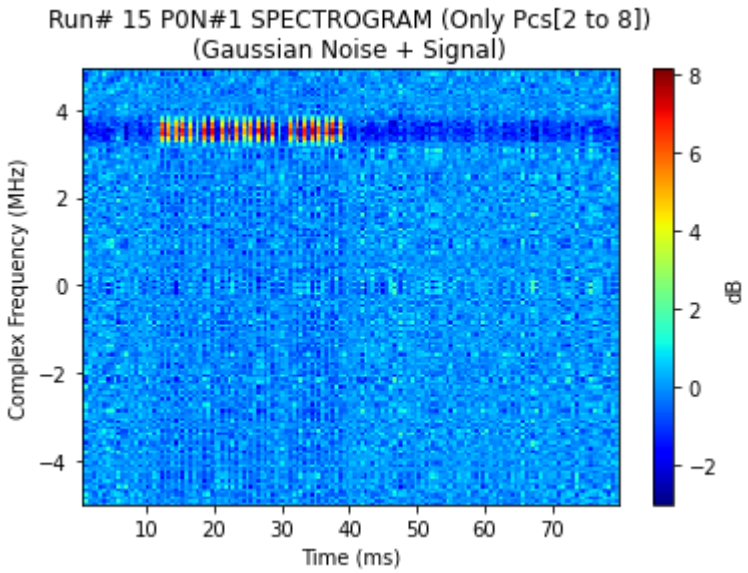

Run# 14 Q3N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

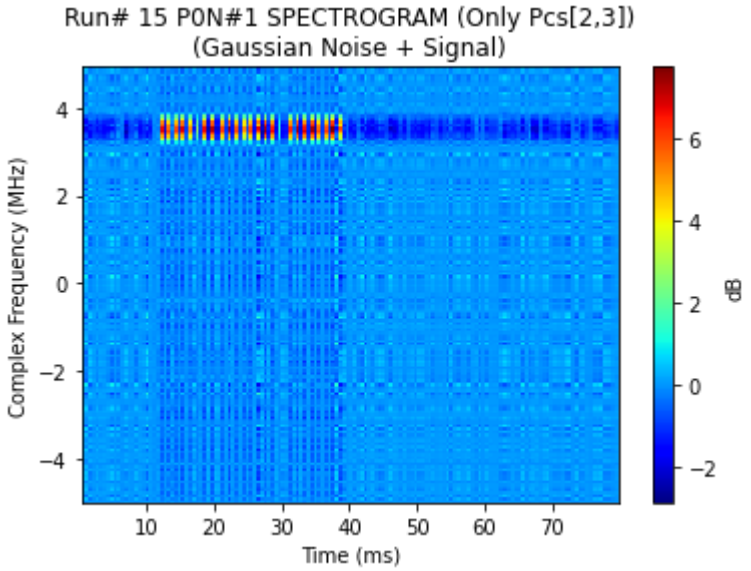

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
−0.0012
−0.0014
−0.0016
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

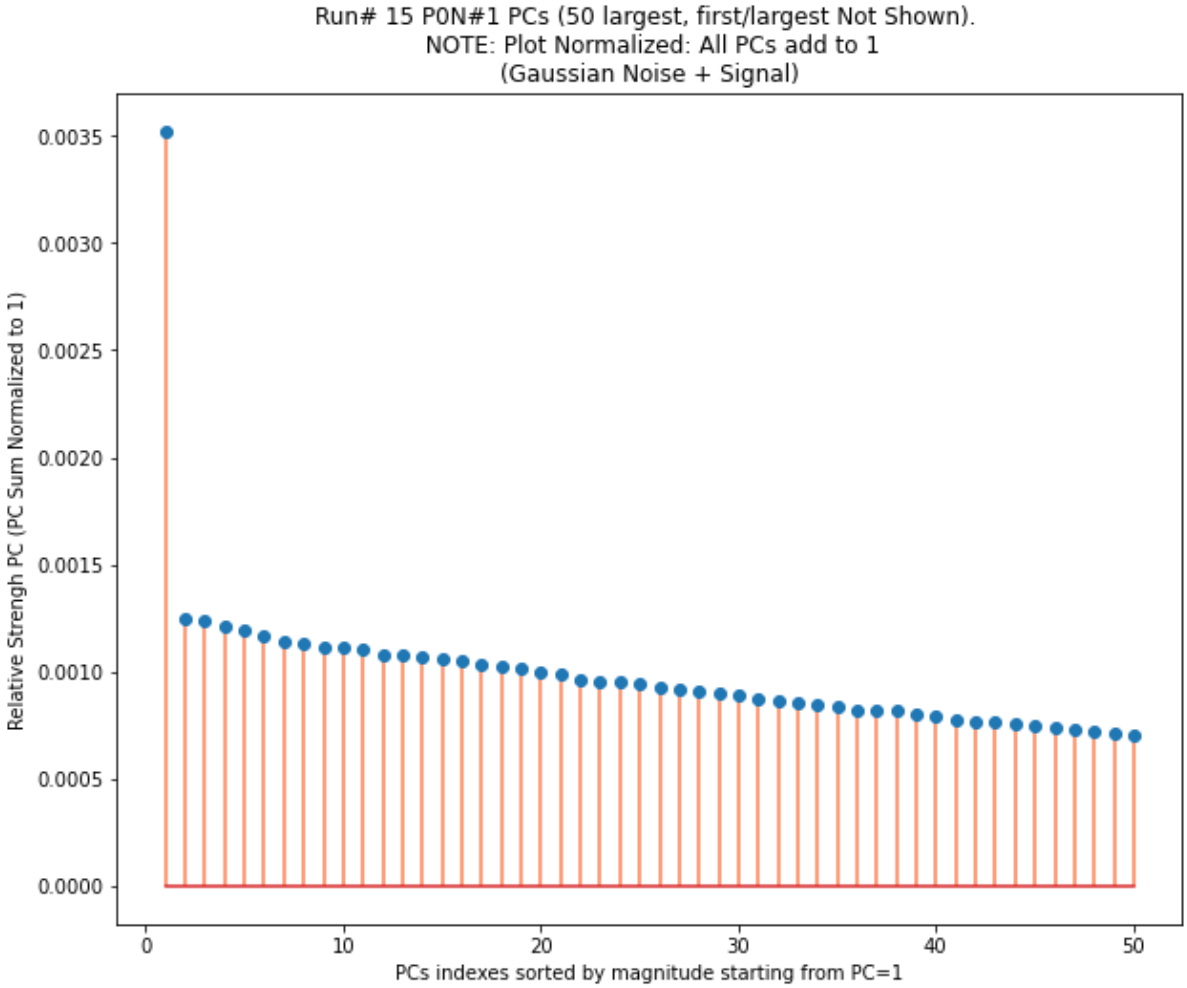

Run# 15 P0N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−134
−136
−138
−140
−142
−144
−146
−148
dB

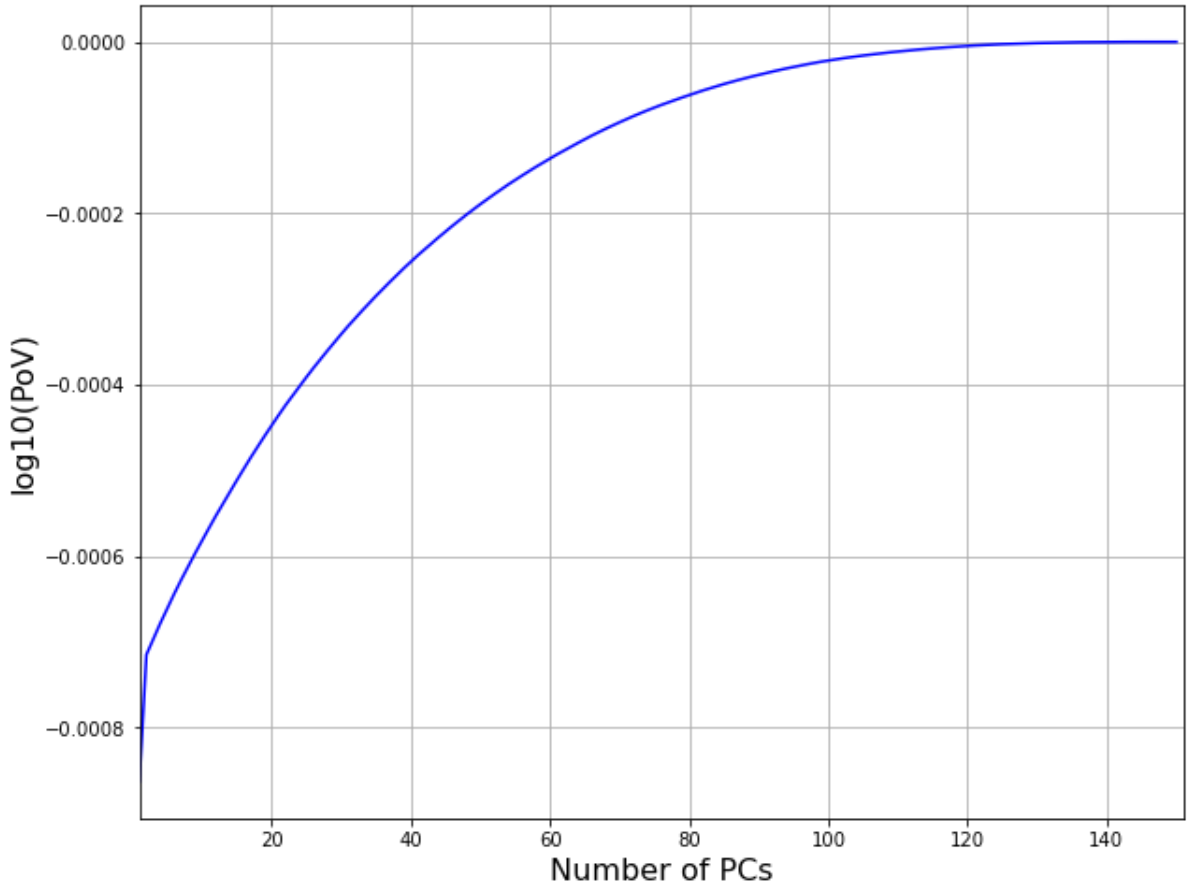

Run# 15 P0N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

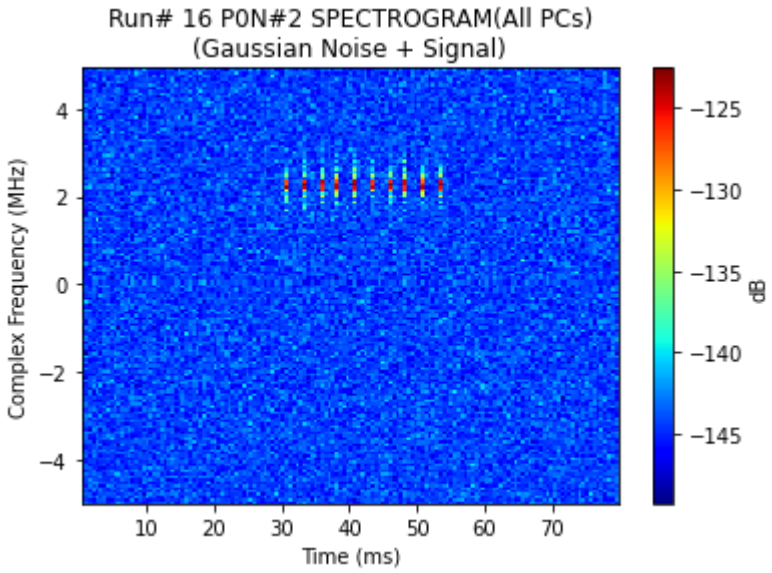

Run# 15 P0N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

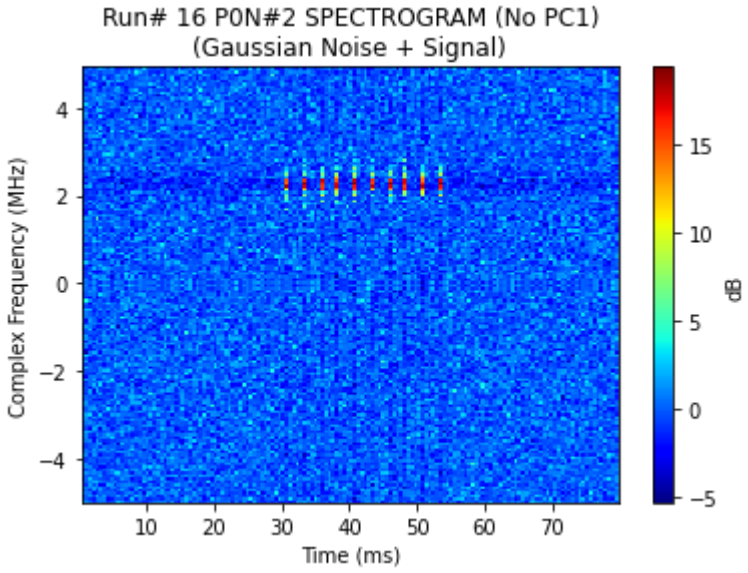

Run# 15 P0N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

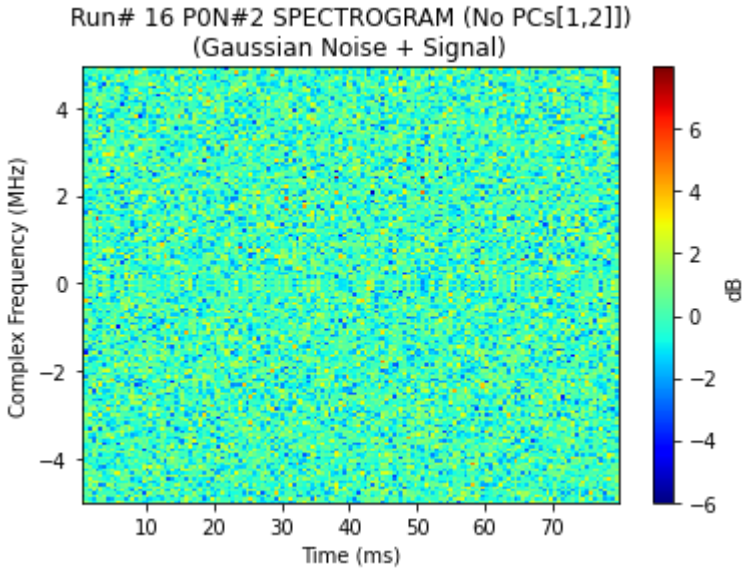

Run# 15 P0N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

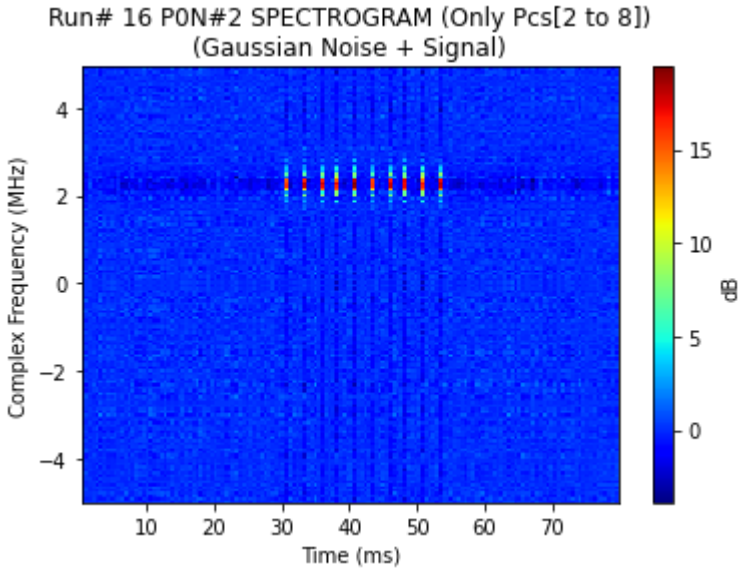

Run# 15 P0N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

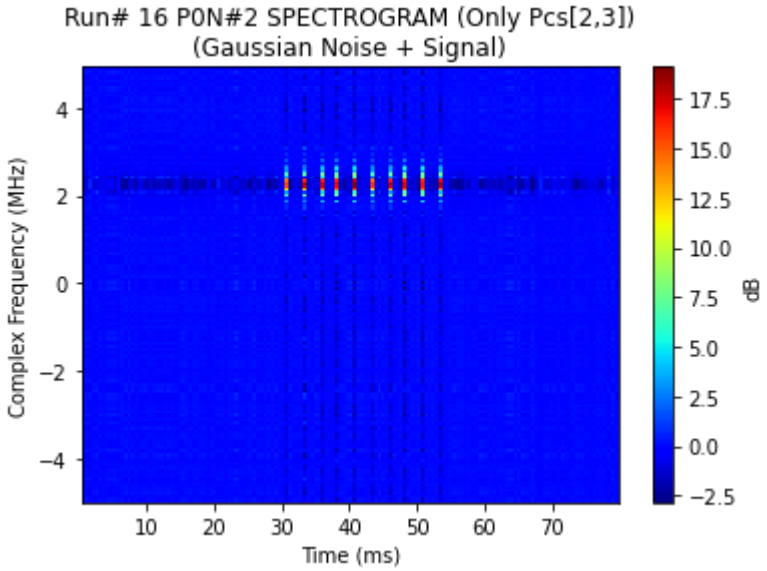

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

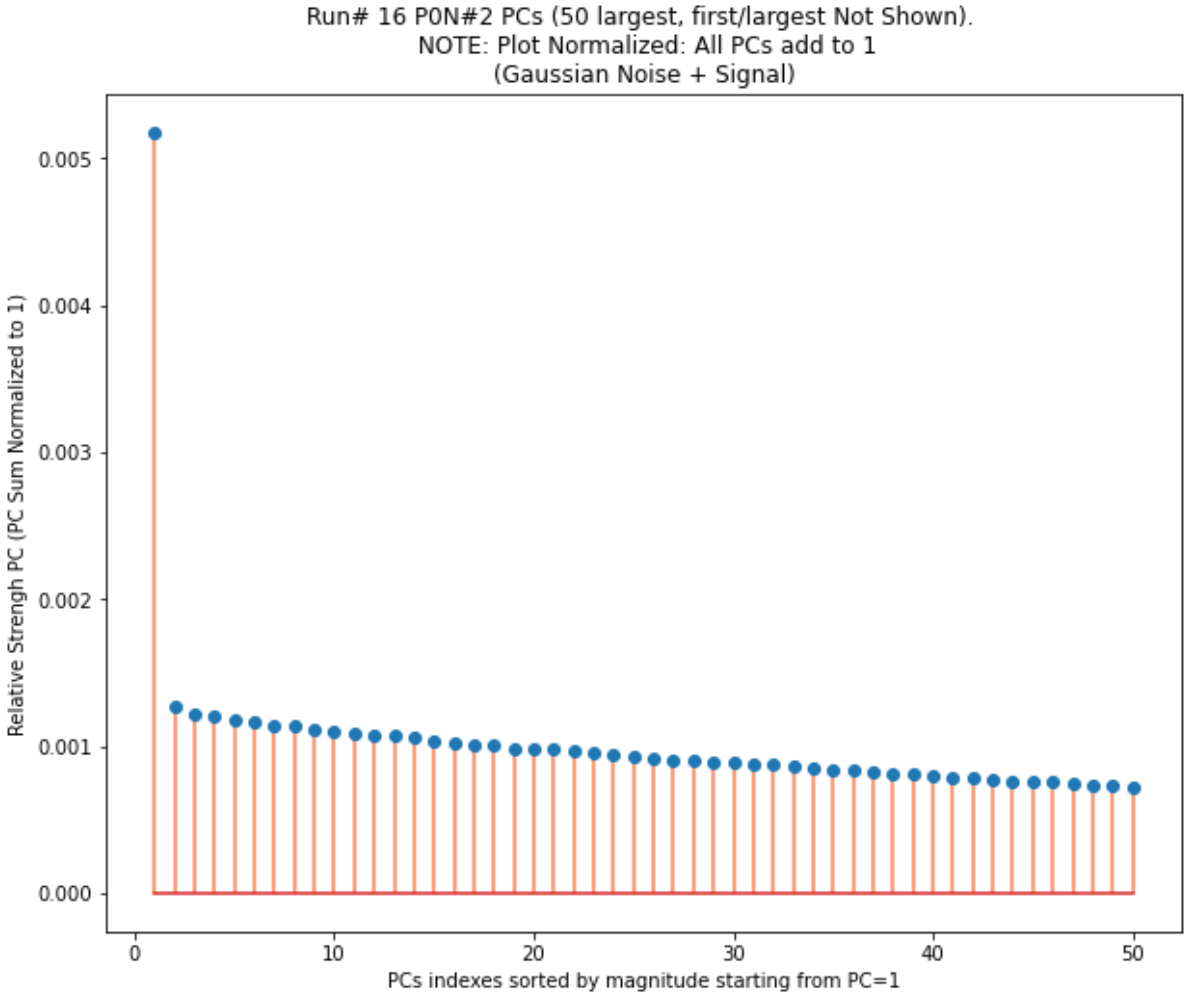

Run# 16 P0N#2 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−125
−130
−135
−140
−145
dB

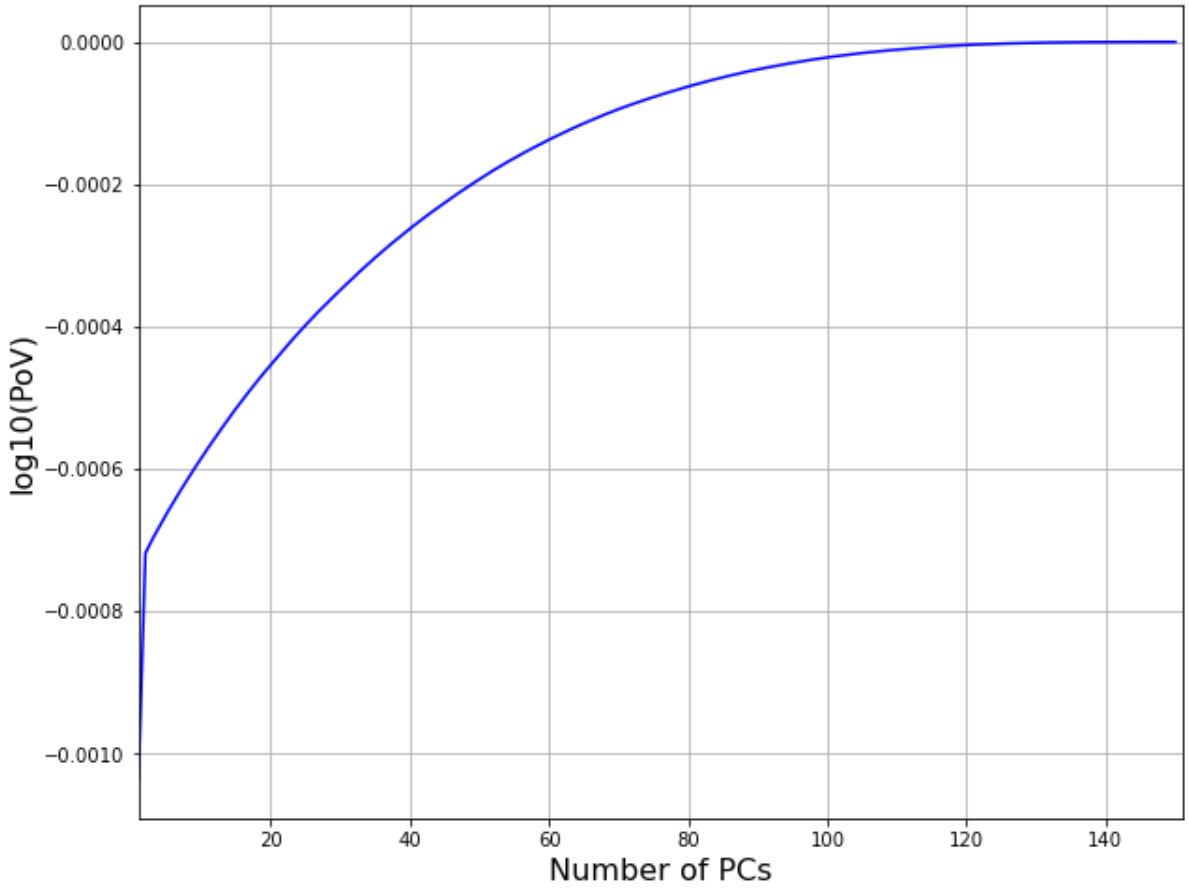

Run# 16 P0N#2 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

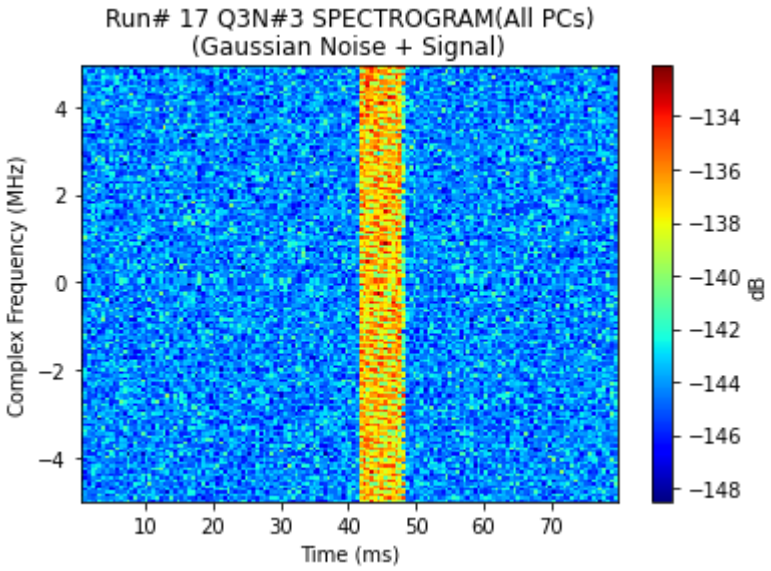

Run# 16 P0N#2 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

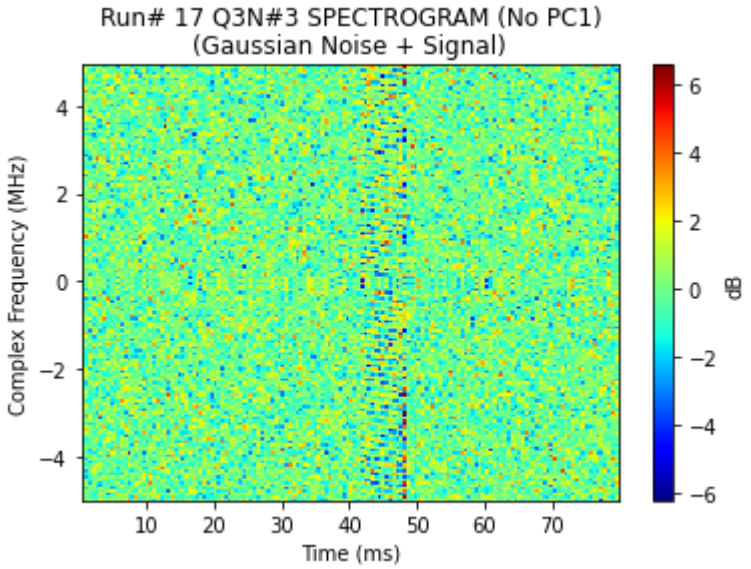

Run# 16 P0N#2 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

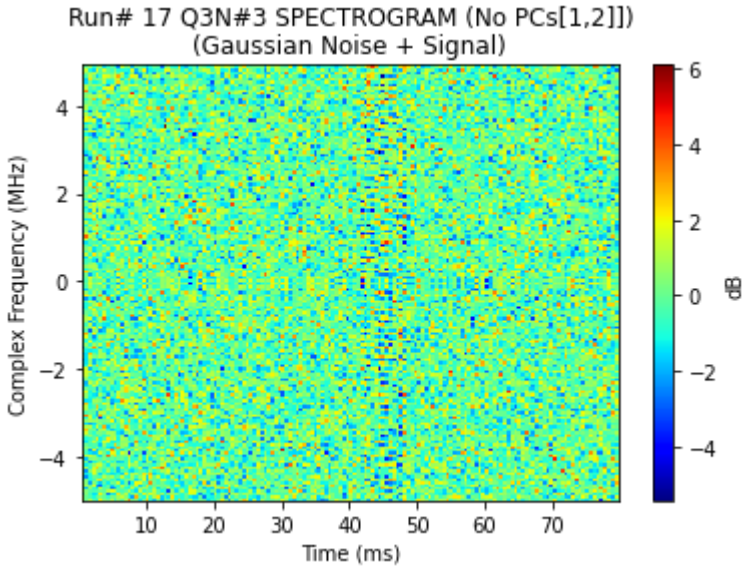

Run# 16 P0N#2 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

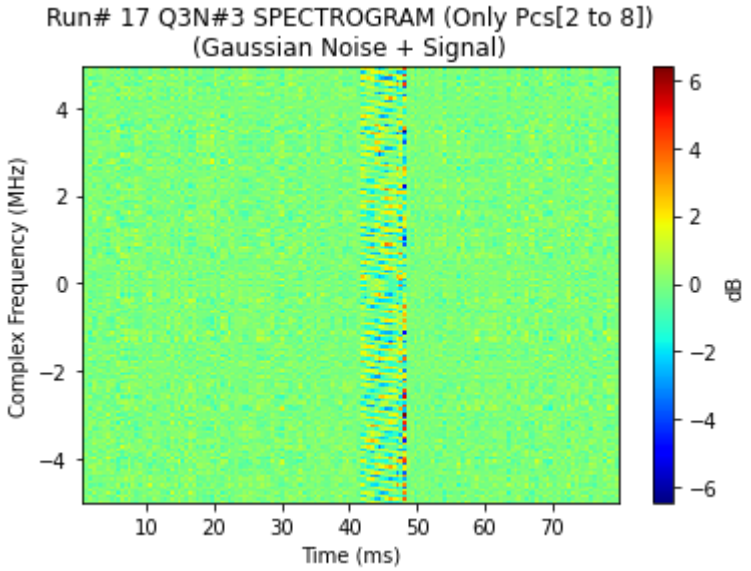

Run# 16 P0N#2 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

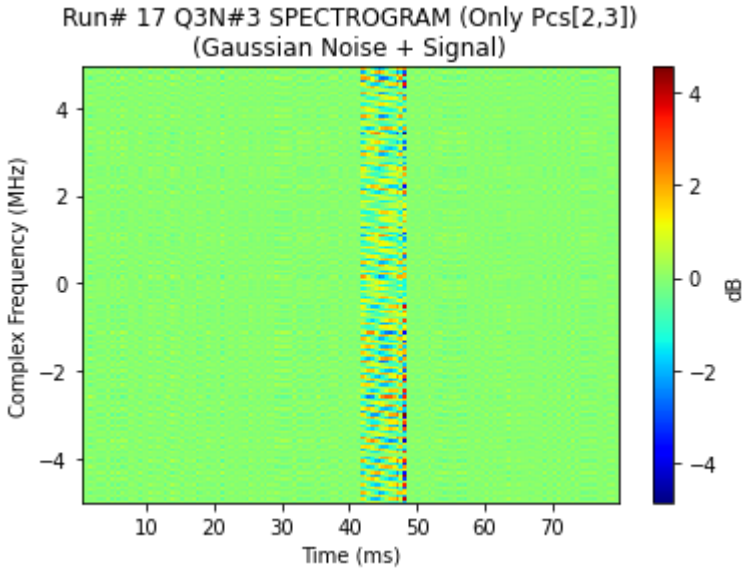

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

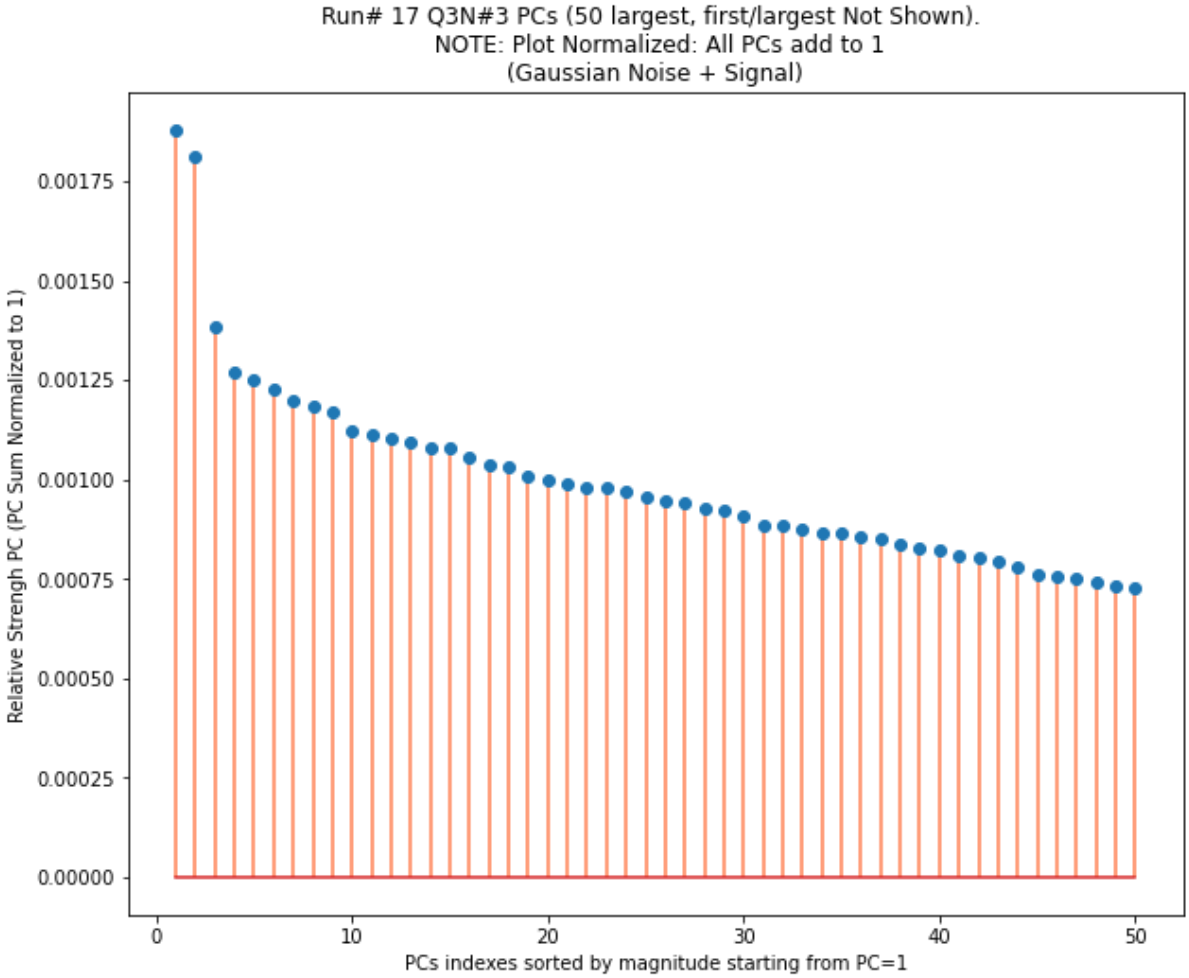

Run# 17 Q3N#3 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−134
−136
−138
−140
−142
−144
−146
−148
dB

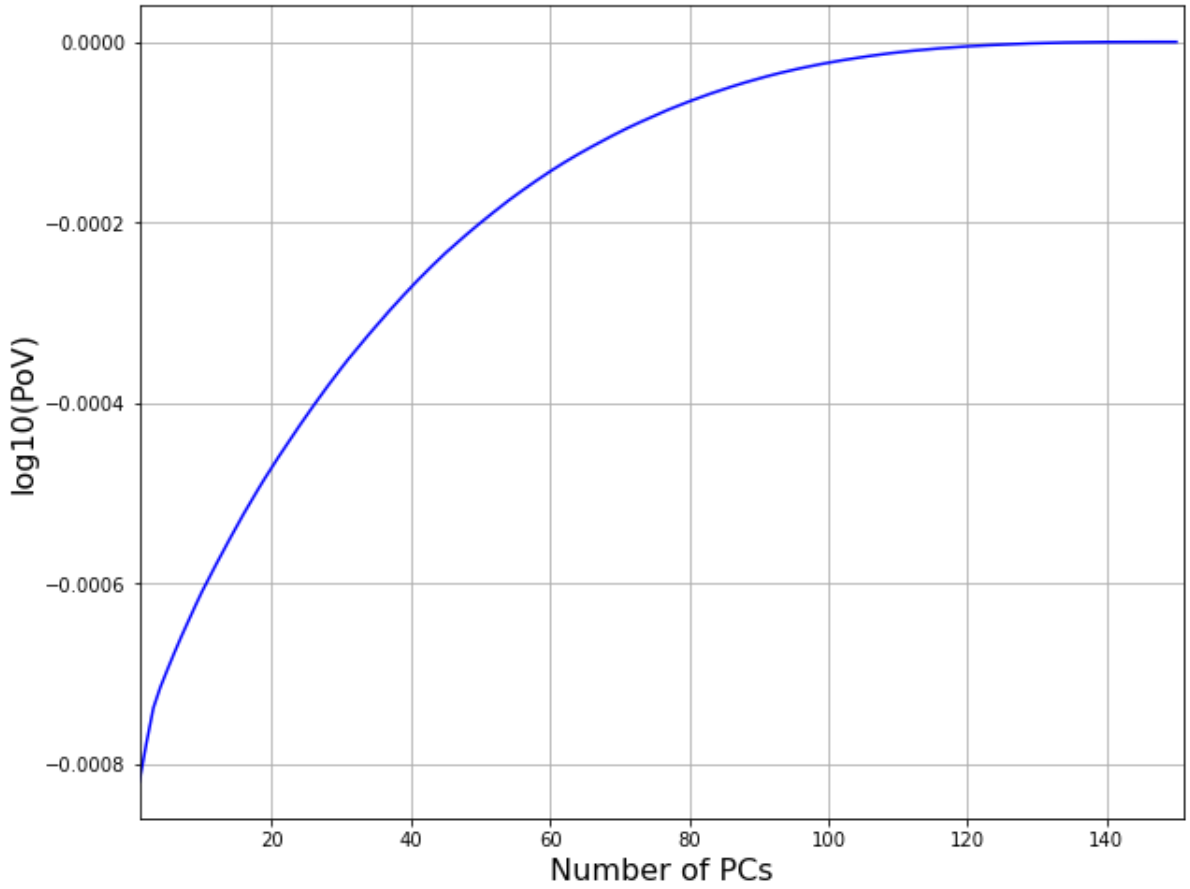

Run# 17 Q3N#3 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

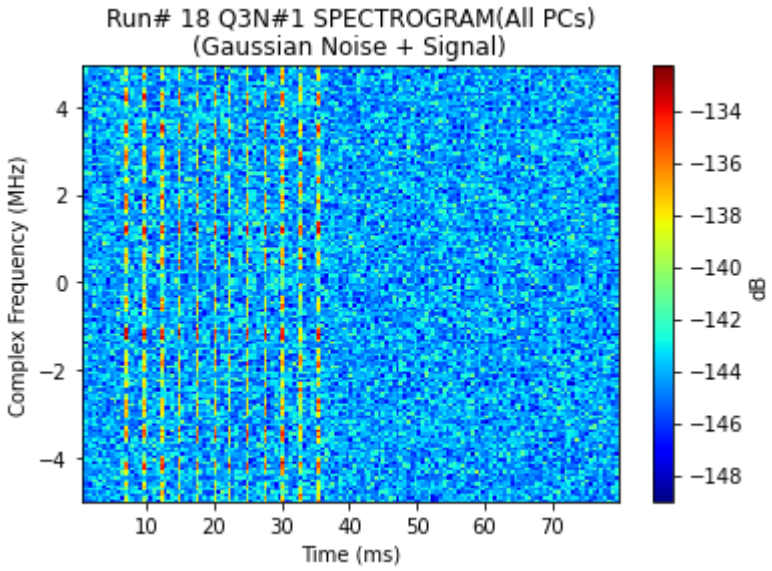

Run# 17 Q3N#3 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

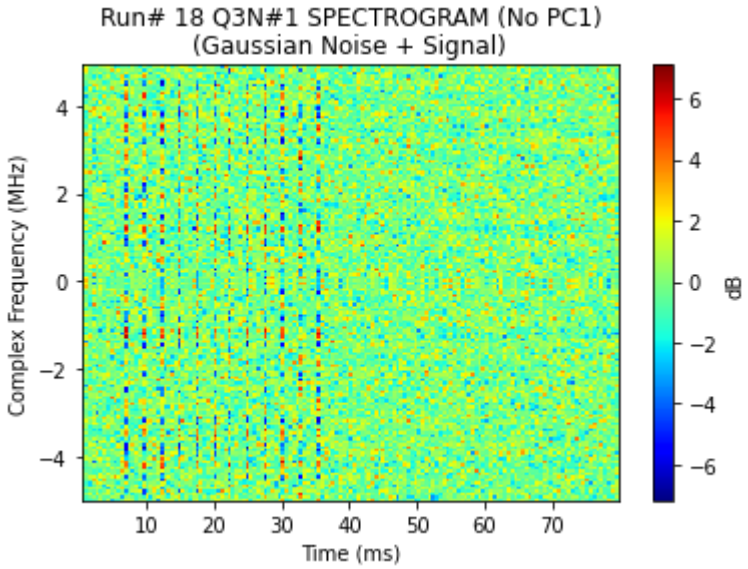

Run# 17 Q3N#3 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

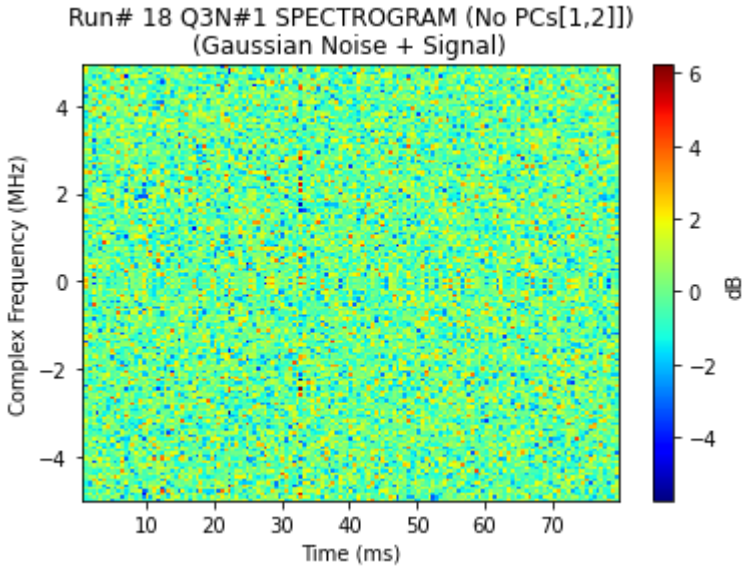

Run# 17 Q3N#3 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

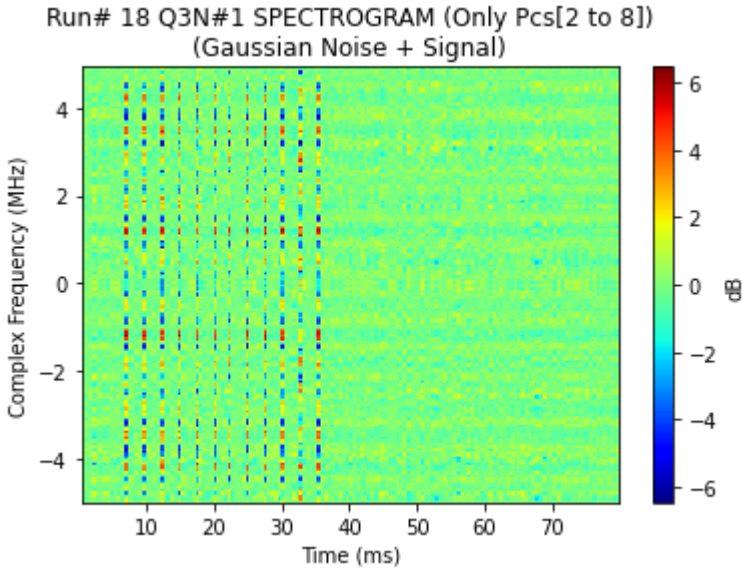

Run# 17 Q3N#3 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

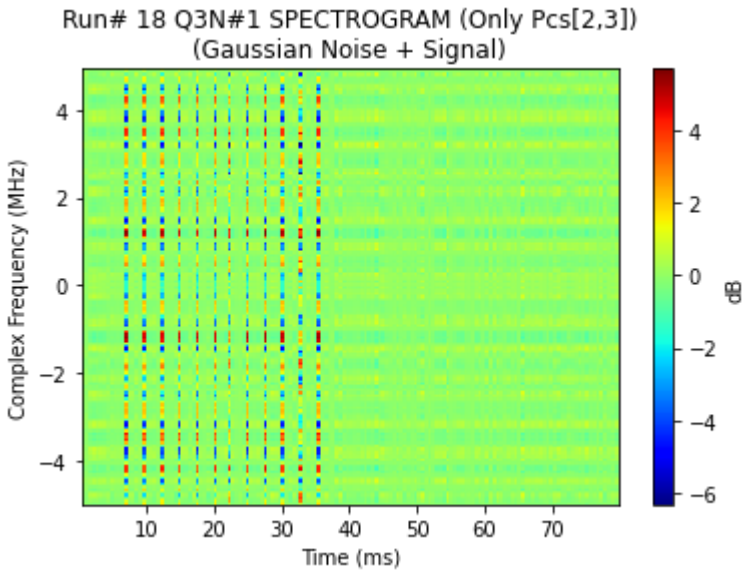

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

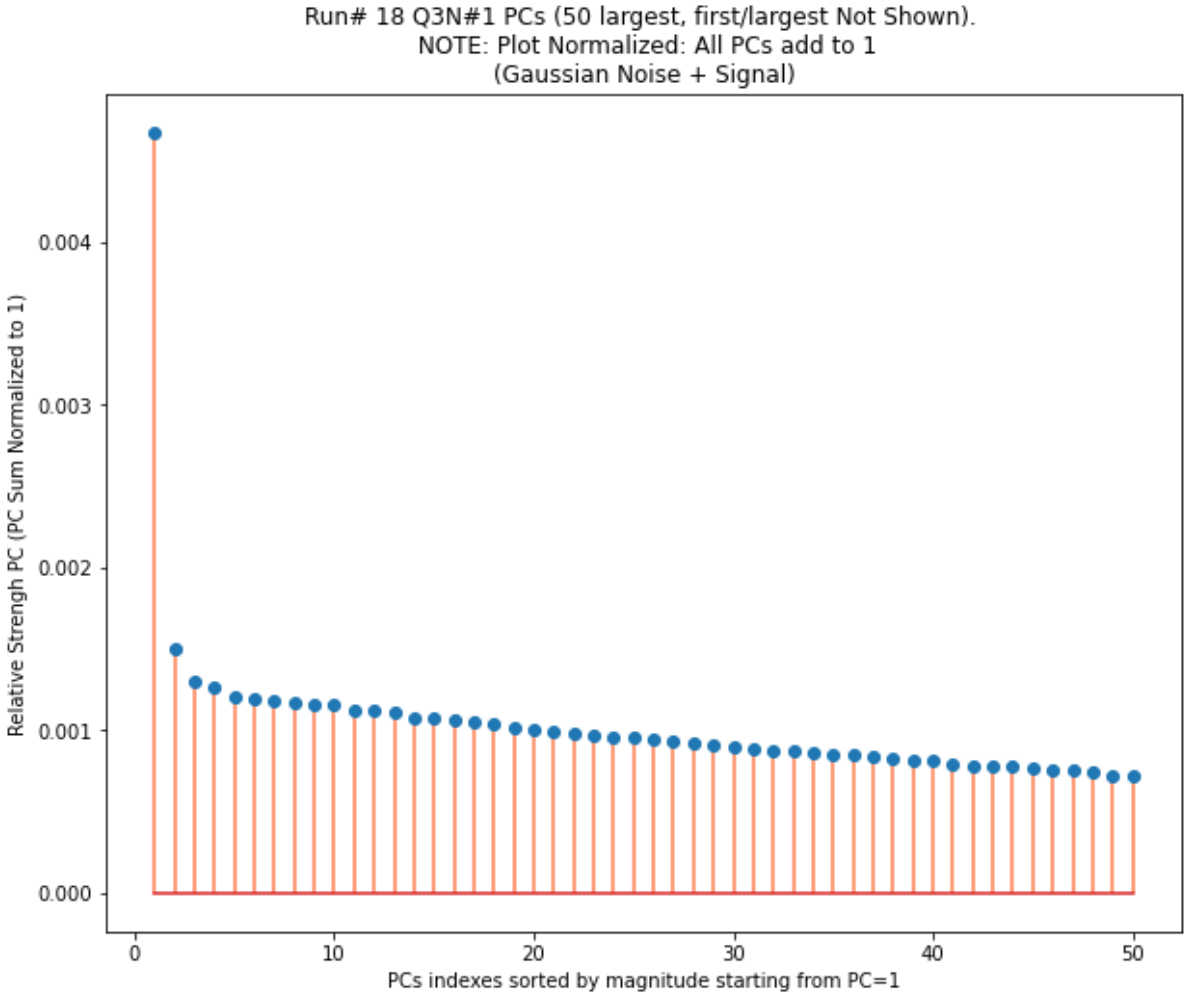

Run# 18 Q3N#1 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−134
−136
−138
−140
−142
−144
−146
−148
dB

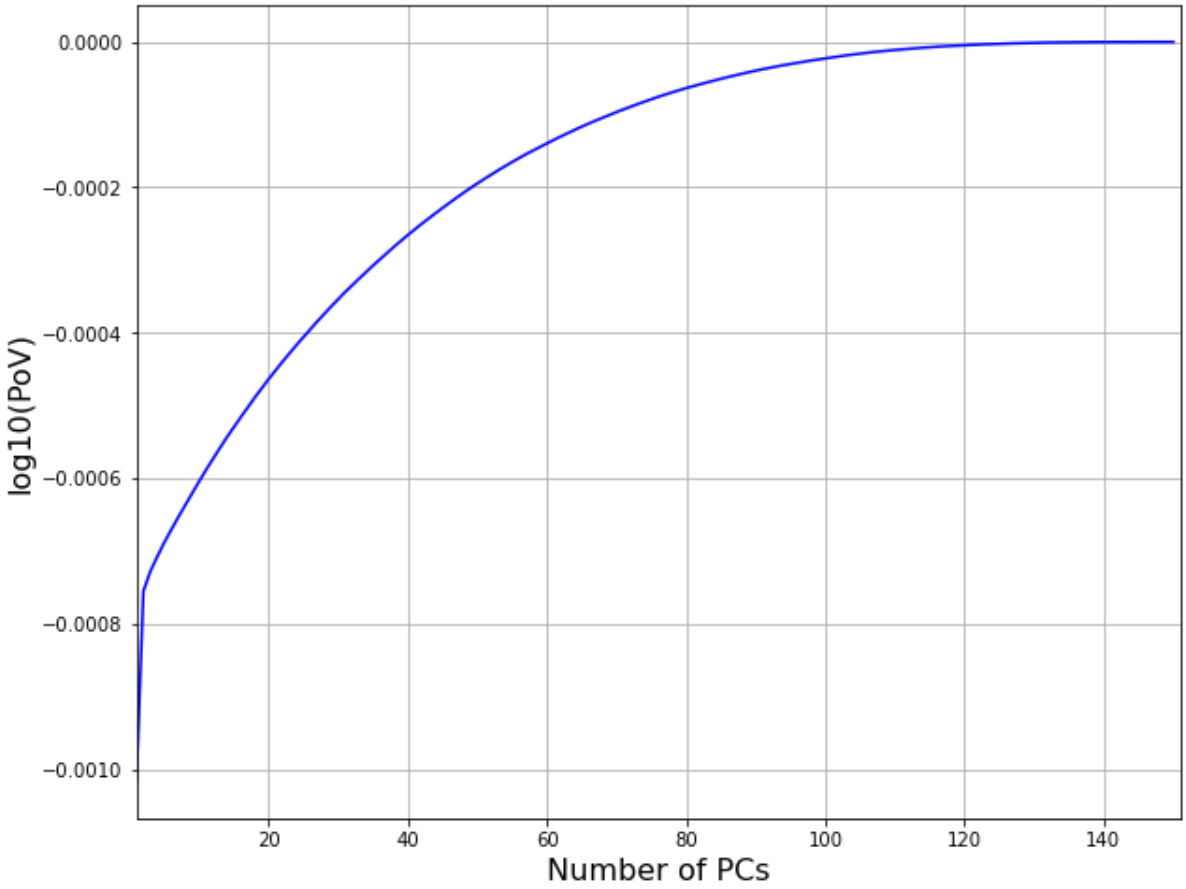

Run# 18 Q3N#1 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

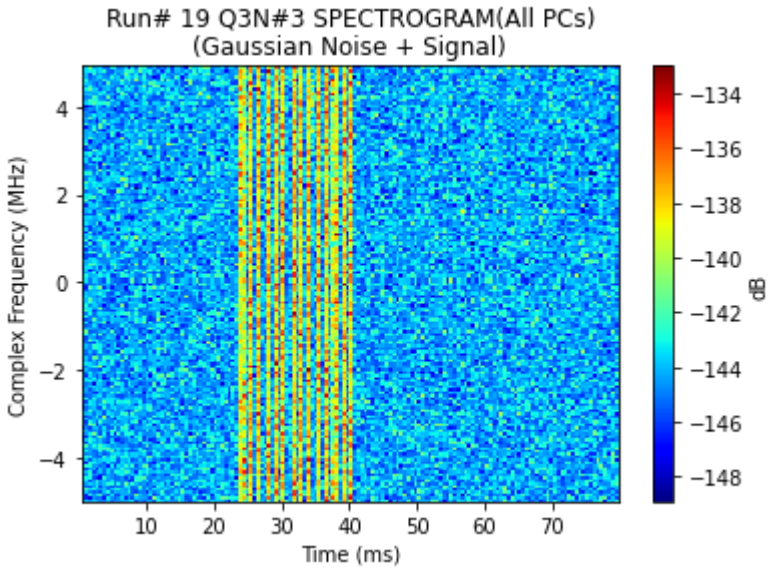

Run# 18 Q3N#1 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

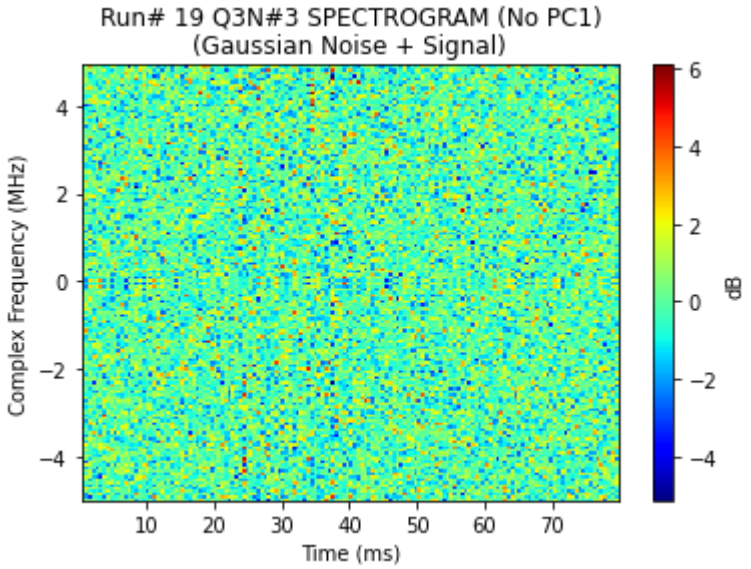

Run# 18 Q3N#1 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

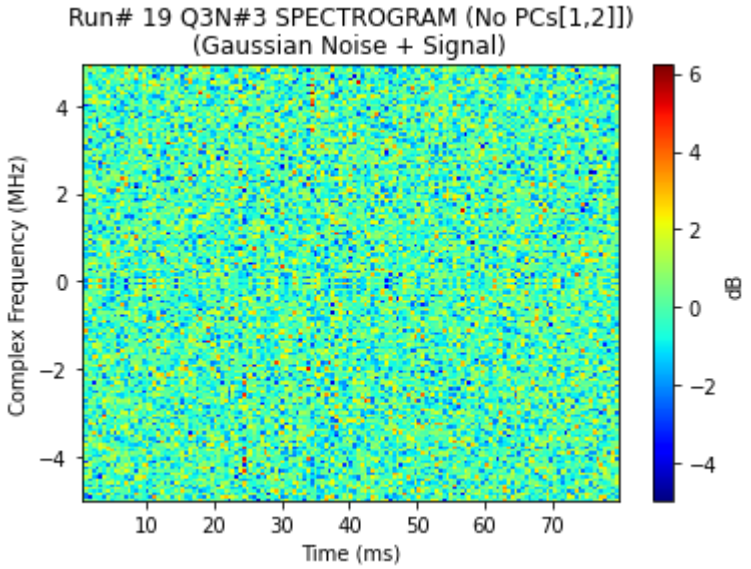

Run# 18 Q3N#1 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

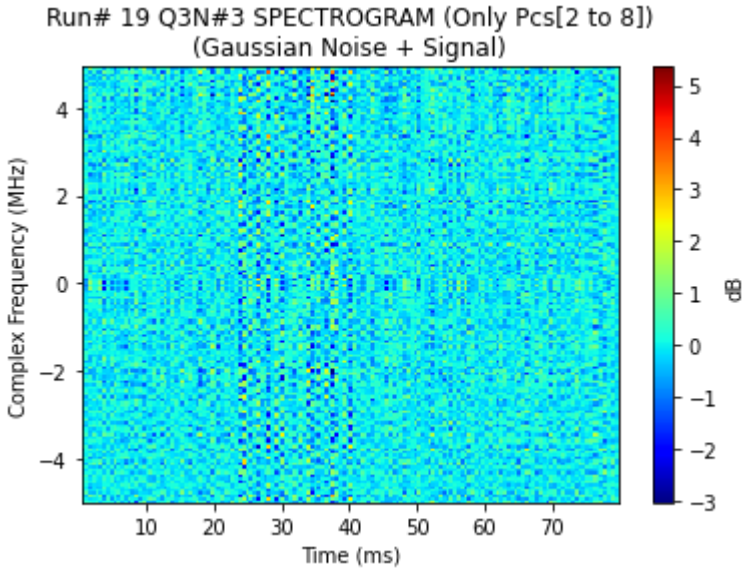

Run# 18 Q3N#1 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

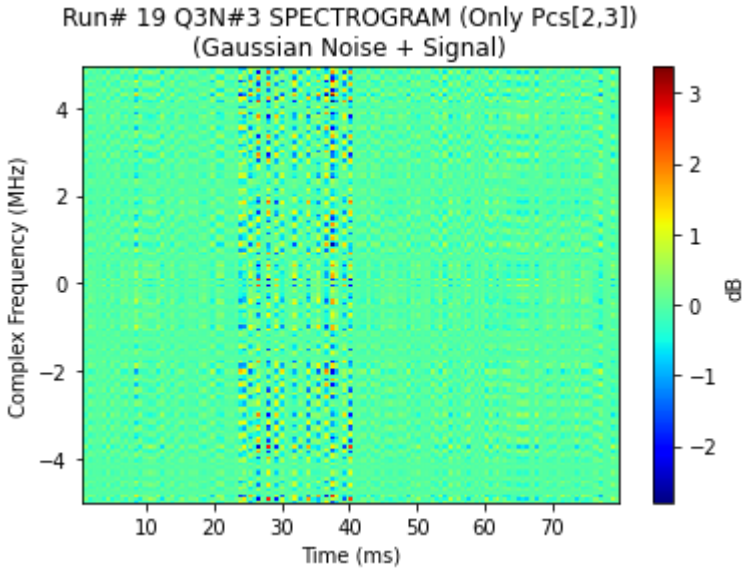

0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

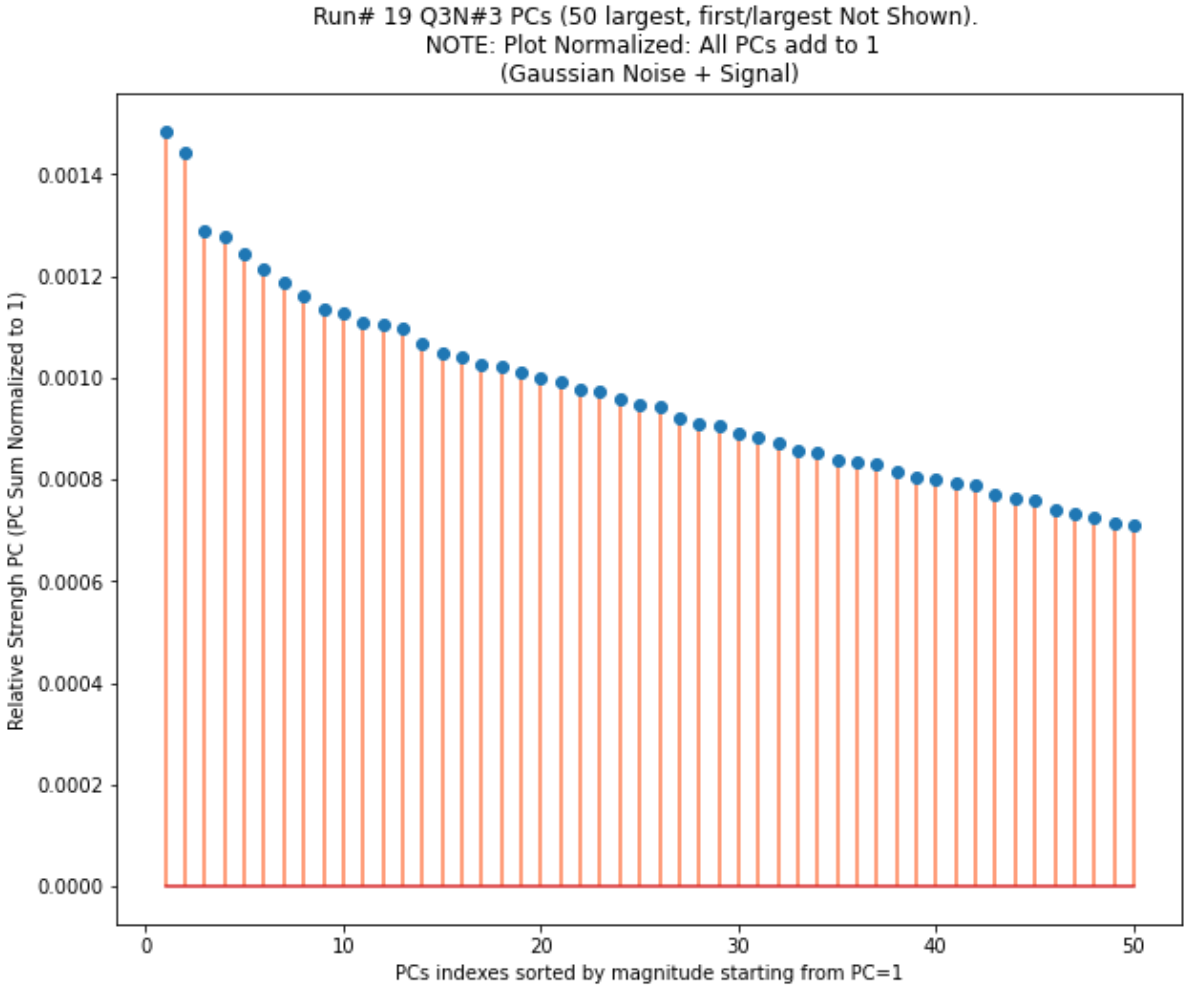

Run# 19 Q3N#3 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
4
2
0
−2
−4
Complex Frequency (MHz)
10
20
30
40
50
60
70
Time (ms)
−134
−136
−138
−140
−142
−144
−146
−148
dB

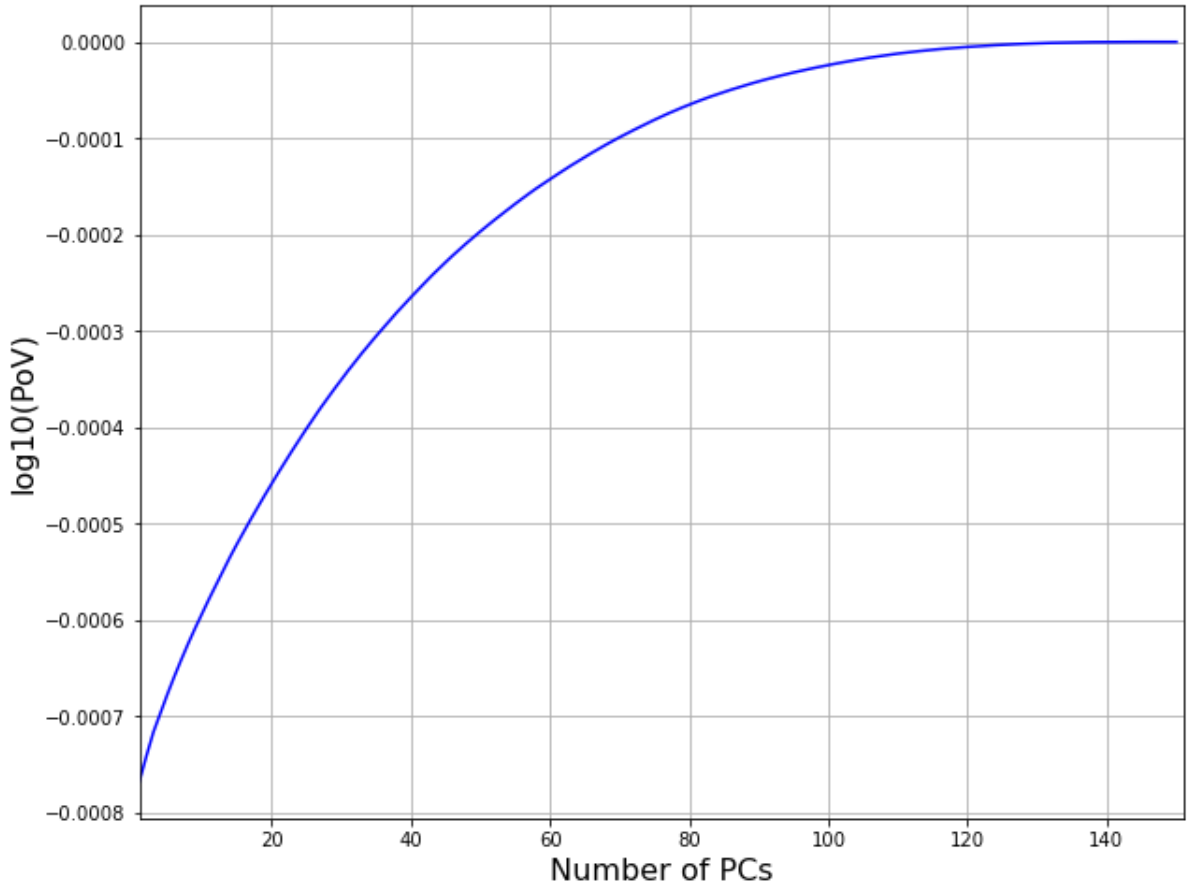

Run# 19 Q3N#3 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

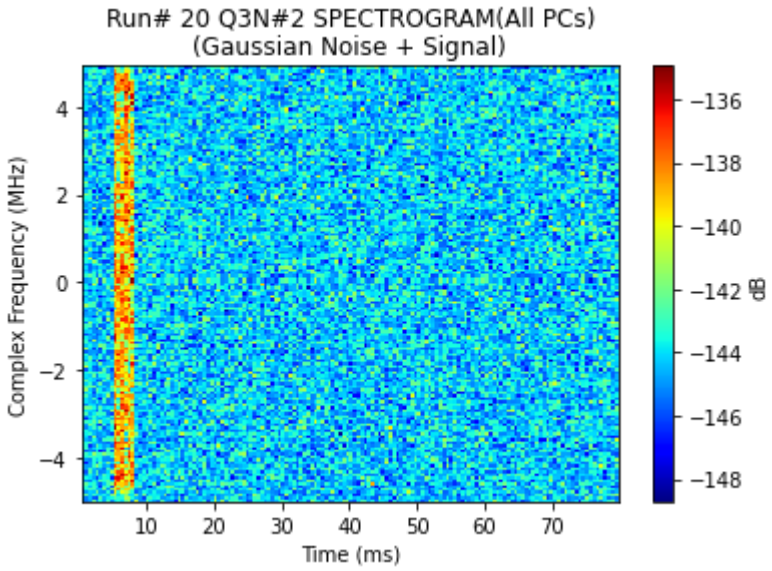

Run# 19 Q3N#3 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

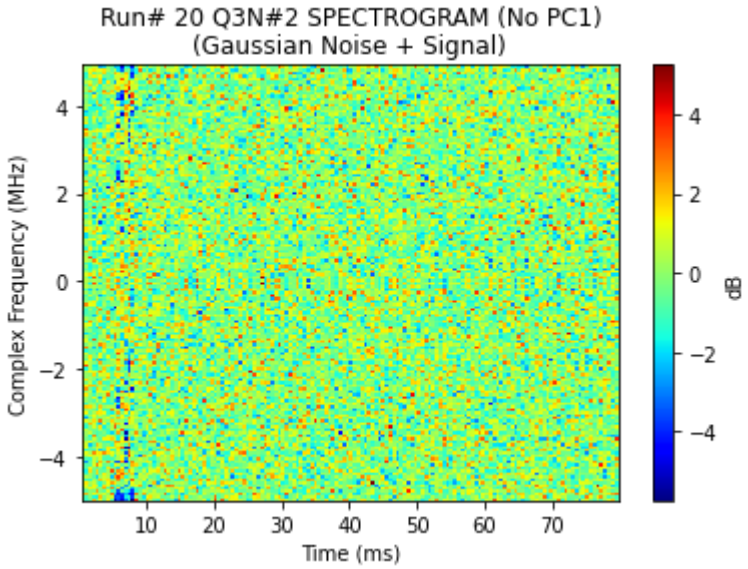

Run# 19 Q3N#3 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

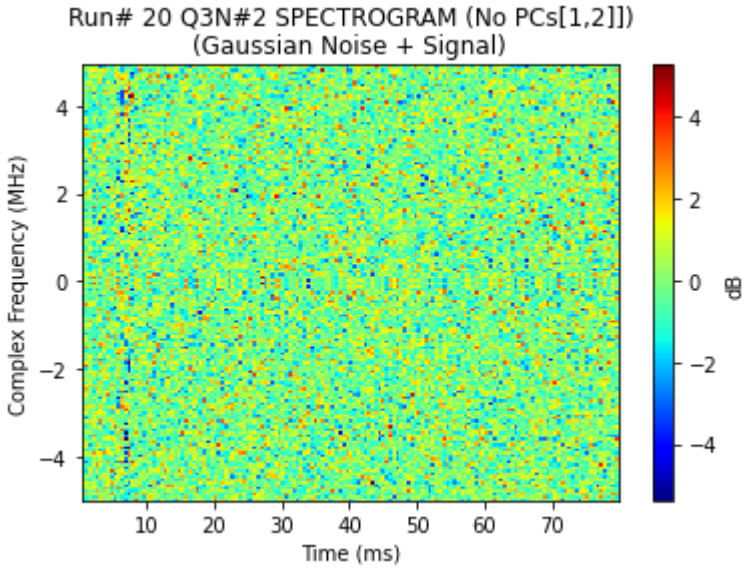

Run# 19 Q3N#3 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB

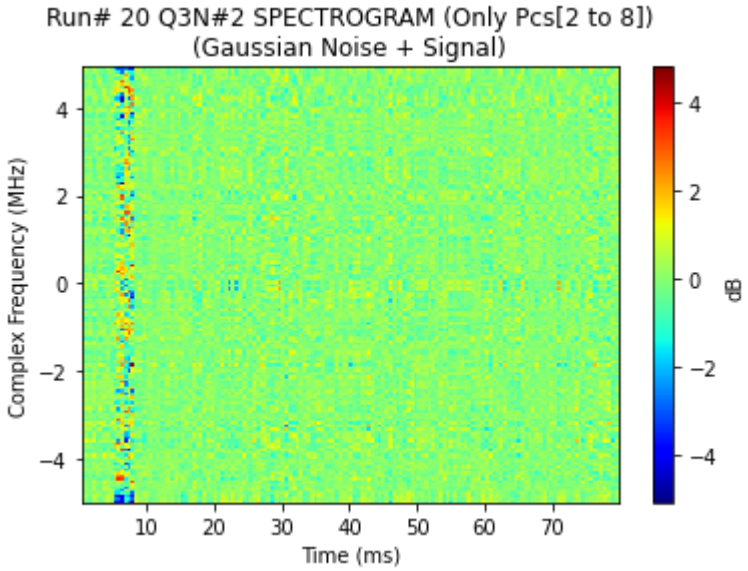

Run# 19 Q3N#3 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1

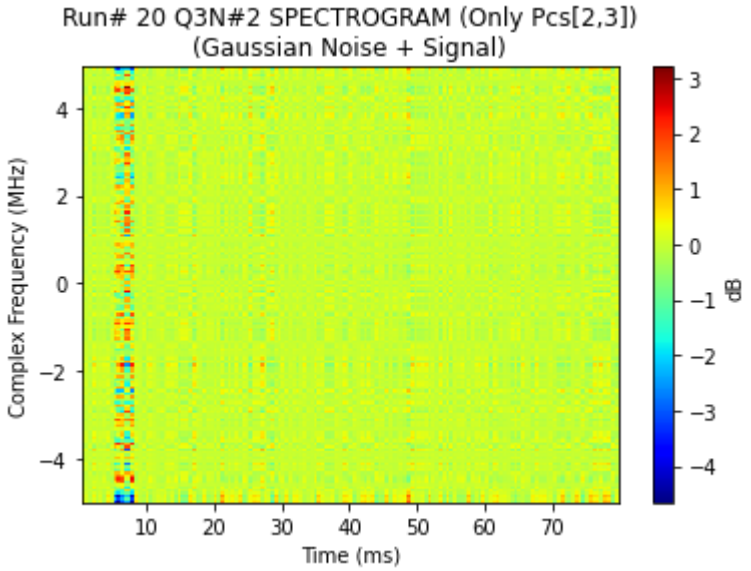

0.0000
−0.0001
−0.0002
−0.0003
−0.0004
−0.0005
−0.0006
−0.0007
−0.0008
log10(PoV)
20
40
60
80
100
120
140
Number of PCs

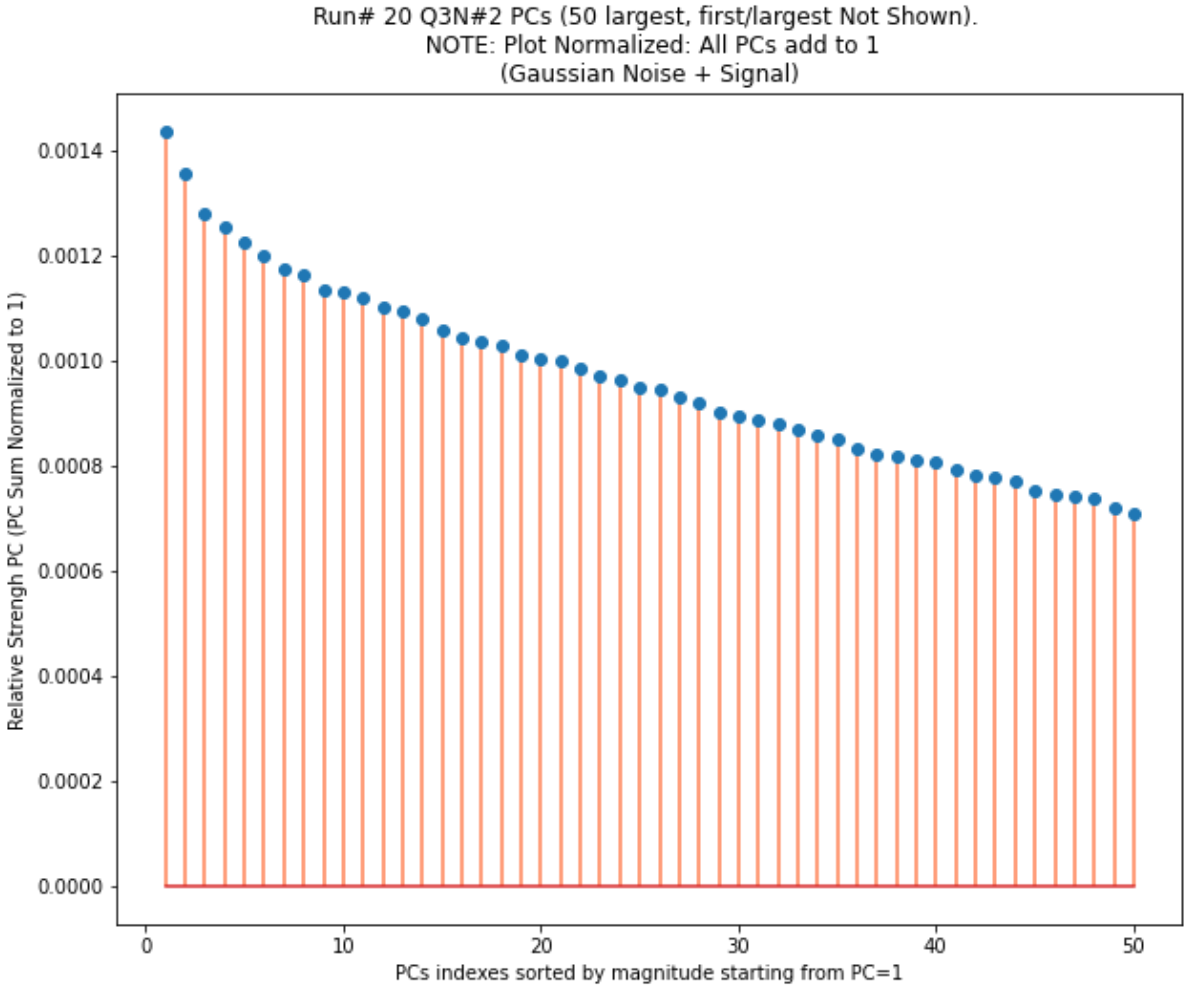

Run# 20 Q3N#2 SPECTROGRAM(All PCs)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
4
2
0
−2
−4
10
20
30
40
50
60
70
Time (ms)
−136
−138
−140
−142
−144
−146
−148
dB

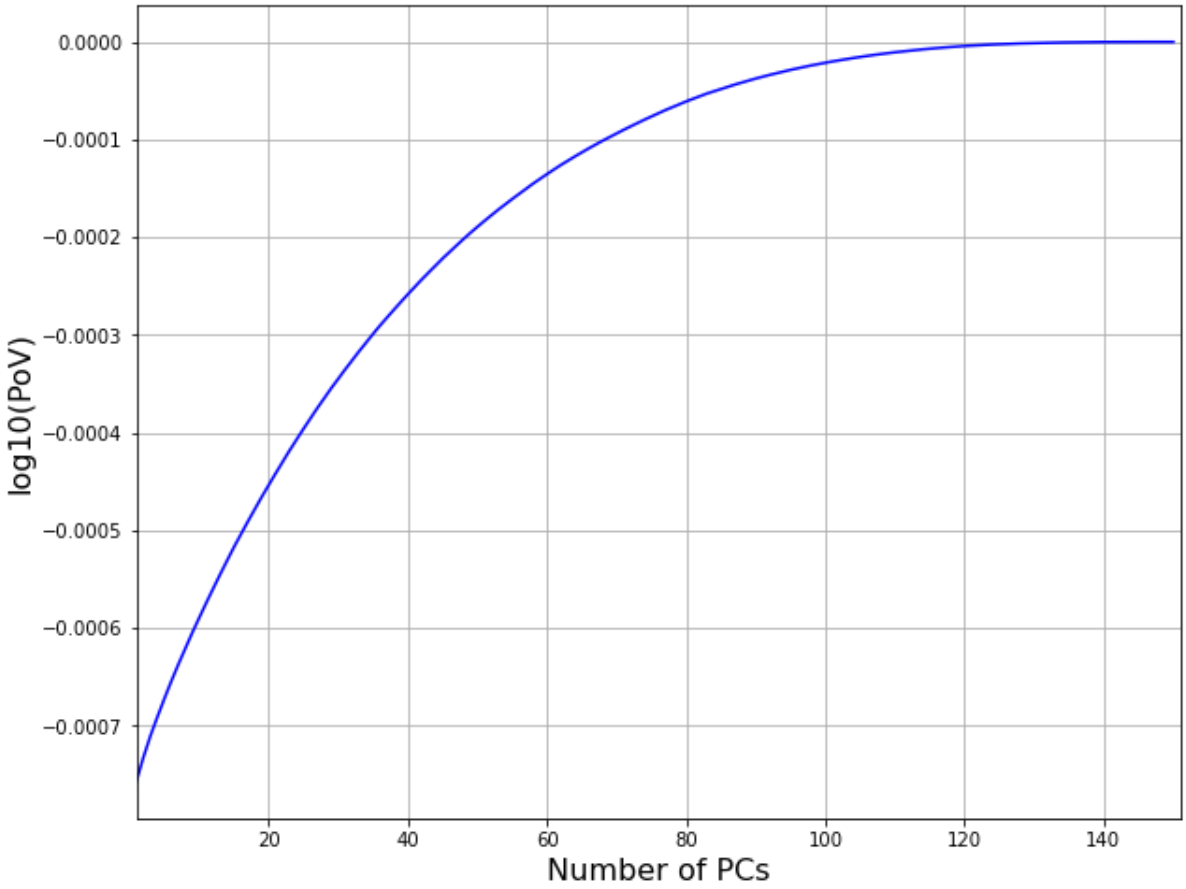

Run# 20 Q3N#2 SPECTROGRAM (No PC1)
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB


Run# 20 Q3N#2 SPECTROGRAM (No PCs[1,2]])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB


Run# 20 Q3N#2 SPECTROGRAM (Only Pcs[2 to 8])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB


Run# 20 Q3N#2 SPECTROGRAM (Only Pcs[2,3])
(Gaussian Noise + Signal)
Complex Frequency (MHz)
Time (ms)
dB


Run# 20 Q3N#2 PCs (50 largest, first/largest Not Shown).
NOTE: Plot Normalized: All PCs add to 1
(Gaussian Noise + Signal)
Relative Strengh PC (PC Sum Normalized to 1)
PCs indexes sorted by magnitude starting from PC=1



Now we will do a Logistic Regression to see if we can detect the presence of any waveform.

We will will access different numbers of PCs to see how the accuracy varies.

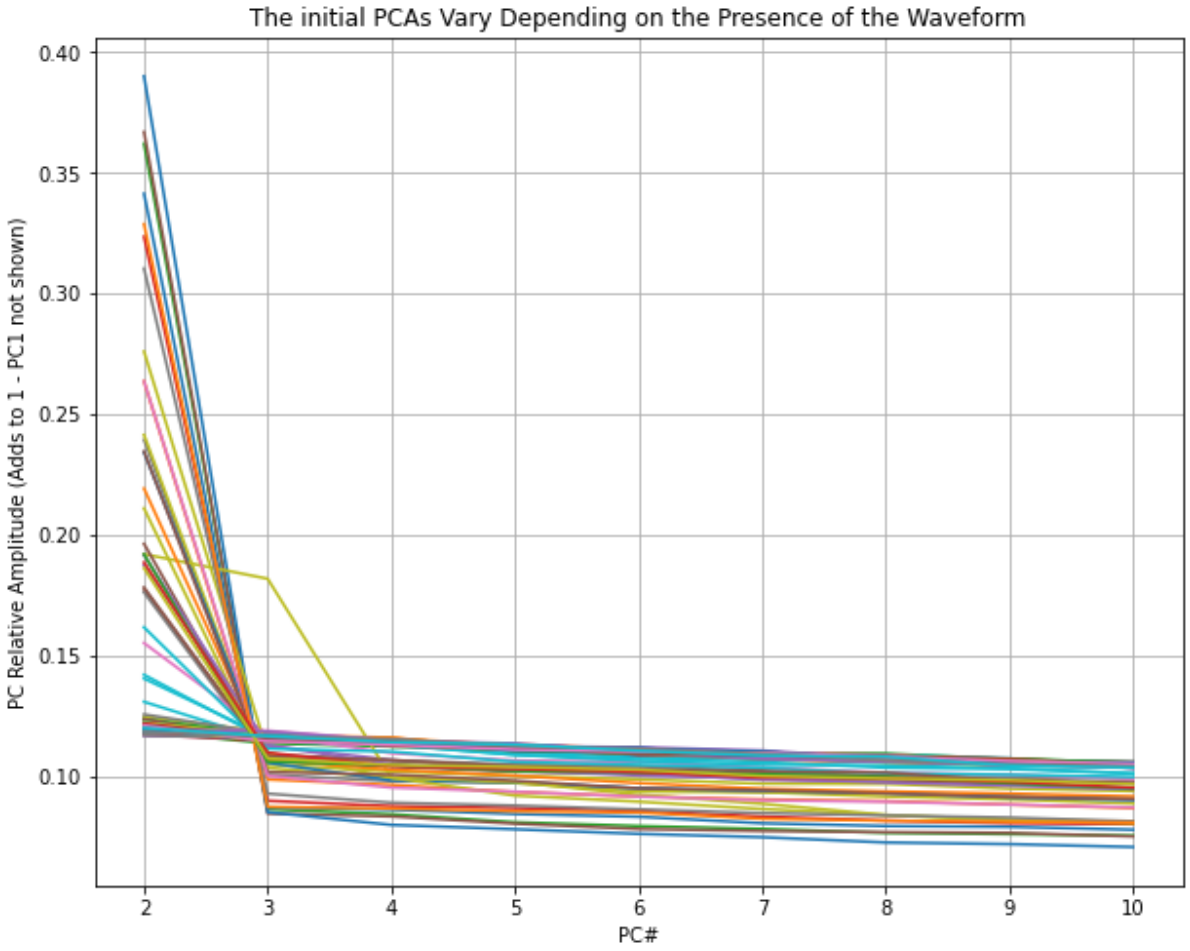
FIRST, we calculate the PCA for all 200 samples

In [10]:
```
nwav         = subsetSignals.shape[0]
MAT_Shi      = np.zeros([nwav, Nfft,Nfft])
MAT_U        = np.zeros([nwav, Nfft,Nfft])
MAT_S        = np.zeros([nwav, Nfft])
MAT_Vh       = np.zeros([nwav, Nfft,Nfft])

for idx in range(nwav):
  #print('***--------------------')
  #print('***Doing for idx=', idx)
  #print('...SNR   :', subsetInfo['SNR'][idx])
  #print('...BinNo :', subsetInfo['BinNo'][idx])
  f, t0, S0 = signal.spectrogram(subsetSignals[idx], fs=10e6, nperseg=Nfft, sc
aling='spectrum', return_onesided=False)
  S0[0:1, :] = S0[1:2, :]
  L = S0.shape[1]/groupby
  S1 = np.reshape(S0[:,:int(L)*groupby], (Nfft,int(L),groupby))
  S = np.amax(S1, axis=-1)
  if flag_make_it_150x150: S=S[:,0:S.shape[0]] #Make is 150x150 Square
  t = t0[groupby-1::groupby]
  fshi = np.fft.fftshift(f/1e6)
  Sshi = np.fft.fftshift(10.*np.log10(S), axes=0)
  MAT_Shi[idx]= Sshi
  MAT_U[idx],MAT_S[idx],MAT_Vh[idx]=np.linalg.svd(Sshi,full_matrices=False);
  #print('...U.shape=', u.shape)
  #print('...S.shape=', s.shape)
  #print('...Vh.shape', vh.shape)
```

Here we print the PCAS. Note that there is variability, specially in the second component.

We will try to exploit this variability to make predictions

In [11]:
```
MINPCA=1
MAXPCA=10

plt.figure(figsize=(10,8))
for idx in range(nwav//2):
  #plt.stem(MAT_S[idx,MINPCA:MAXPCA]/np.sum(MAT_S[idx,MINPCA:MAXPCA]), use_line_collection=True)
  plt.plot(np.arange(MINPCA+1,MAXPCA+1),MAT_S[idx,MINPCA:MAXPCA]/np.sum(MAT_S[idx,MINPCA:MAXPCA]))
plt.grid()
plt.title("The initial PCAs Vary Depending on the Presence of the Waveform")
plt.xlabel("PC#");
plt.ylabel("PC Relative Amplitude (Adds to 1 - PC1 not shown)");
```



Now we will do the Logistic Regression to detect the signal (binary prediction). Because we are using only 200 samples (a file with 200 samples is 2.5 GB large), we will use KFolding.

We will assess many different numbers of PCs to see if more PCs help.

In [12]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.linear_model  import LogisticRegression
from sklearn.model_selection import KFold

y = subsetRadarStatus.ravel()
X = MAT_S #The PCs

# Create a K-fold object
nfold = 5
kf    = KFold(n_splits=nfold, shuffle=True)
kf.get_n_splits(X)

# Number of PCs to try
ncomp_test = np.array([1,2,3,4,5,6,7,8,9,10,20,30,40,50,100,X.shape[1]])
#ncomp_test = np.arange(2,2  +1)
num_nc     = len(ncomp_test)
print("We will try %d # of PCs: "%num_nc, ncomp_test)
print('X.shape=', X.shape)

# Accuracy:  acc[icomp,ifold]  is test accuracy when
# using `ncomp = ncomp_test[icomp]` in fold `ifold`.
acc      = np.zeros((num_nc,nfold))
acc_comp = np.zeros((num_nc))

# Loop over number of components to test
for icomp, ncomp in enumerate(ncomp_test):
    print(":::------------------------------------------------")
    print(":::Trying (icomp,ncomp) = (", icomp, ',', ncomp, ')')
    # Look over the folds
    for ifold, I in enumerate(kf.split(X)):
        Itr, Its = I

        # Xtr, Xts, ytr, yts = ...
        Xtr = X[Itr, 0:ncomp]; ytr = y[Itr];
        Xts = X[Its, 0:ncomp]; yts = y[Its];

        # Use a logistic regression classifier
        logreg = LogisticRegression(multi_class='auto', solver='lbfgs', max_it
er=10000)
        logreg.fit(Xtr, ytr)

        yprob         = logreg.predict_proba(Xts)
        yprob_max     = np.amax(yprob,axis=1)
        yprob_max_ind = (yprob == yprob_max[:, None]).astype(int)
        yprob_1d      = np.zeros(yts.shape).astype(int)
        #There is probably a more direct way to do this
        for idx in range(1,yprob_max_ind.shape[1]):
          yprob_1d += (yprob_max_ind[:,idx]*idx).astype(int)
        acc_cf = (yts == yprob_1d).astype(int)
        #print('yts=',yts)
        #print('yprob_1d=',yprob_1d)
        #acc_cf = (yts == ypred).astype(int)
        acc[icomp, ifold] = np.mean(acc_cf)
        print("...kfold",ifold,"ncomp=",ncomp,"Accur=",acc[icomp,ifold])
    #end of inner for()
    acc_comp[icomp] = np.mean(acc[icomp,:])
```

```
    print("***Mean accuracy folding was",acc_comp[icomp],"(nc=",ncomp,")")
#end of outer for()
```

```
We will try 16 # of PCs:  [  1   2   3   4   5   6   7   8   9  10  20  30  4
0  50 100 150]
X.shape= (200, 150)
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 0 , 1 )
...kfold 0 ncomp= 1 Accur= 0.425
...kfold 1 ncomp= 1 Accur= 0.55
...kfold 2 ncomp= 1 Accur= 0.475
...kfold 3 ncomp= 1 Accur= 0.525
...kfold 4 ncomp= 1 Accur= 0.4
***Mean accuracy folding was 0.475 (nc= 1 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 1 , 2 )
...kfold 0 ncomp= 2 Accur= 0.95
...kfold 1 ncomp= 2 Accur= 0.9
...kfold 2 ncomp= 2 Accur= 0.9
...kfold 3 ncomp= 2 Accur= 0.925
...kfold 4 ncomp= 2 Accur= 0.875
***Mean accuracy folding was 0.9099999999999999 (nc= 2 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 2 , 3 )
...kfold 0 ncomp= 3 Accur= 0.925
...kfold 1 ncomp= 3 Accur= 0.825
...kfold 2 ncomp= 3 Accur= 0.925
...kfold 3 ncomp= 3 Accur= 0.95
...kfold 4 ncomp= 3 Accur= 0.975
***Mean accuracy folding was 0.9199999999999999 (nc= 3 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 3 , 4 )
...kfold 0 ncomp= 4 Accur= 0.9
...kfold 1 ncomp= 4 Accur= 0.9
...kfold 2 ncomp= 4 Accur= 0.9
...kfold 3 ncomp= 4 Accur= 1.0
...kfold 4 ncomp= 4 Accur= 0.925
***Mean accuracy folding was 0.925 (nc= 4 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 4 , 5 )
...kfold 0 ncomp= 5 Accur= 0.9
...kfold 1 ncomp= 5 Accur= 0.925
...kfold 2 ncomp= 5 Accur= 0.85
...kfold 3 ncomp= 5 Accur= 0.95
...kfold 4 ncomp= 5 Accur= 0.975
***Mean accuracy folding was 0.9199999999999999 (nc= 5 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 5 , 6 )
...kfold 0 ncomp= 6 Accur= 0.875
...kfold 1 ncomp= 6 Accur= 0.975
...kfold 2 ncomp= 6 Accur= 0.925
...kfold 3 ncomp= 6 Accur= 0.95
...kfold 4 ncomp= 6 Accur= 0.95
***Mean accuracy folding was 0.9350000000000002 (nc= 6 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 6 , 7 )
...kfold 0 ncomp= 7 Accur= 0.975
...kfold 1 ncomp= 7 Accur= 0.975
...kfold 2 ncomp= 7 Accur= 0.875
...kfold 3 ncomp= 7 Accur= 0.975
```

```
...kfold 4 ncomp= 7 Accur= 0.875
***Mean accuracy folding was 0.9350000000000002 (nc= 7 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 7 , 8 )
...kfold 0 ncomp= 8 Accur= 0.95
...kfold 1 ncomp= 8 Accur= 0.975
...kfold 2 ncomp= 8 Accur= 0.875
...kfold 3 ncomp= 8 Accur= 0.875
...kfold 4 ncomp= 8 Accur= 0.95
***Mean accuracy folding was 0.925 (nc= 8 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 8 , 9 )
...kfold 0 ncomp= 9 Accur= 0.95
...kfold 1 ncomp= 9 Accur= 0.925
...kfold 2 ncomp= 9 Accur= 0.925
...kfold 3 ncomp= 9 Accur= 0.9
...kfold 4 ncomp= 9 Accur= 0.95
***Mean accuracy folding was 0.9299999999999999 (nc= 9 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 9 , 10 )
...kfold 0 ncomp= 10 Accur= 0.95
...kfold 1 ncomp= 10 Accur= 0.95
...kfold 2 ncomp= 10 Accur= 0.9
...kfold 3 ncomp= 10 Accur= 0.9
...kfold 4 ncomp= 10 Accur= 1.0
***Mean accuracy folding was 0.9399999999999998 (nc= 10 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 10 , 20 )
...kfold 0 ncomp= 20 Accur= 0.95
...kfold 1 ncomp= 20 Accur= 0.975
...kfold 2 ncomp= 20 Accur= 0.875
...kfold 3 ncomp= 20 Accur= 0.9
...kfold 4 ncomp= 20 Accur= 0.975
***Mean accuracy folding was 0.9349999999999999 (nc= 20 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 11 , 30 )
...kfold 0 ncomp= 30 Accur= 0.975
...kfold 1 ncomp= 30 Accur= 0.975
...kfold 2 ncomp= 30 Accur= 0.95
...kfold 3 ncomp= 30 Accur= 0.875
...kfold 4 ncomp= 30 Accur= 0.95
***Mean accuracy folding was 0.945 (nc= 30 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 12 , 40 )
...kfold 0 ncomp= 40 Accur= 0.95
...kfold 1 ncomp= 40 Accur= 0.925
...kfold 2 ncomp= 40 Accur= 0.925
...kfold 3 ncomp= 40 Accur= 0.925
...kfold 4 ncomp= 40 Accur= 1.0
***Mean accuracy folding was 0.945 (nc= 40 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 13 , 50 )
...kfold 0 ncomp= 50 Accur= 0.95
...kfold 1 ncomp= 50 Accur= 0.95
...kfold 2 ncomp= 50 Accur= 0.95
...kfold 3 ncomp= 50 Accur= 0.925
...kfold 4 ncomp= 50 Accur= 0.95
```

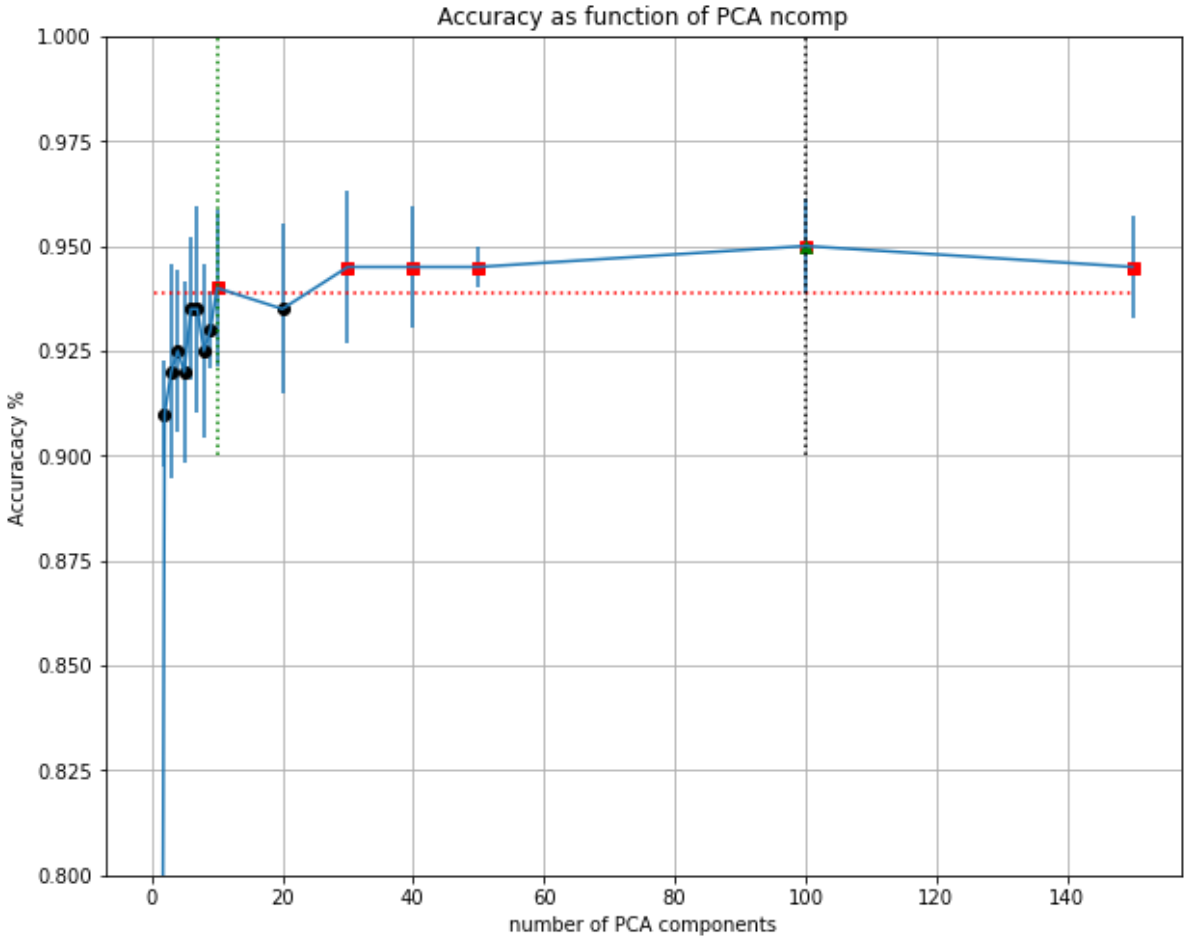
```
***Mean accuracy folding was 0.945 (nc= 50 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 14 , 100 )
...kfold 0 ncomp= 100 Accur= 0.975
...kfold 1 ncomp= 100 Accur= 0.925
...kfold 2 ncomp= 100 Accur= 0.975
...kfold 3 ncomp= 100 Accur= 0.925
...kfold 4 ncomp= 100 Accur= 0.95
***Mean accuracy folding was 0.95 (nc= 100 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 15 , 150 )
...kfold 0 ncomp= 150 Accur= 0.925
...kfold 1 ncomp= 150 Accur= 0.925
...kfold 2 ncomp= 150 Accur= 0.975
...kfold 3 ncomp= 150 Accur= 0.925
...kfold 4 ncomp= 150 Accur= 0.975
***Mean accuracy folding was 0.945 (nc= 150 )
```

Results were not bad at all. We got 95% of accuracy. Below we print the results and choose the number of PCs using the SE RULE and the NORMAL RULE.

Please note that some waveforms may be harder to detect that others. To check that we will not a Multi-class Logistic Regression later

In [13]:
```
acc_mean = np.mean(acc, axis=1)
acc_se   = np.std(acc, axis=1) / np.sqrt(nfold-1)
plt.figure(figsize=(10,8))
plt.errorbar(ncomp_test, acc_mean, yerr=acc_se)

# Optimal order with the normal rule
# Optimal order with one SE rule
# Find the max R^2
imax    = np.argmax(acc_mean)
acc_tgt = acc_mean[imax] - acc_se[imax]

# Find the Lowest delay above the target
I = np.where(acc_mean >= acc_tgt)[0]
iopt = I[0]
dopt = ncomp_test[iopt]
print(imax, iopt, dopt, acc_tgt)
# Plot the line at the target level
plt.plot([acc_mean[0],ncomp_test[len(ncomp_test)-1]],[acc_tgt,acc_tgt],'r:')
plt.plot(ncomp_test, acc_mean, 'ko')
plt.plot(ncomp_test[I], acc_mean[I], 'rs')
plt.plot(ncomp_test[imax], acc_mean[imax], 'g^')
# Plot the line at the optimal model order
plt.plot([dopt,dopt], [0.9,1], 'g:')
plt.plot([ncomp_test[imax],ncomp_test[imax]], [0.9,1], 'k:')

plt.title('Accuracy as function of PCA ncomp')
plt.xlabel('number of PCA components')
plt.ylabel('Accuracacy %')
plt.ylim((0.8,1))
plt.grid()


# Print results
print("SE     RULE: estimated optimal order #pcs=%d"%dopt)
print("NORMAL RULE: estimated optimal order #pcs=%d"%ncomp_test[imax])
```

```
14 9 10 0.9388196601125011
SE     RULE: estimated optimal order #pcs=10
NORMAL RULE: estimated optimal order #pcs=100
```



NOW we will do a multi-class Logistic Regression. Intead of checking for the presence of the waveform or not immersed in the gaussian noise, we will try to detect what specific wavefor is present.

We will see that the results are not as accurante as in the binary (waveform present or not) case.

FIRST, we need to crate the labels. There will be 6 labels, one for no signal and 5 for the possible signals that may be being transmitted.

In [14]:
```
y = subsetRadarStatus.ravel()
WLAB = ['NOISE_ONLY','P0N#1','P0N#2','Q3N#1','Q3N#2', 'Q3N#3']
#aux=subsetInfo['BinNo'];print("WAVEFORMS   in the file:", aux.unique());
I1=np.where(subsetInfo['BinNo']==WLAB[1])
I2=np.where(subsetInfo['BinNo']==WLAB[2])
I3=np.where(subsetInfo['BinNo']==WLAB[3])
I4=np.where(subsetInfo['BinNo']==WLAB[4])
I5=np.where(subsetInfo['BinNo']==WLAB[5])
y6 = np.zeros(X.shape[0])
y6[I1] = 1
y6[I2] = 2
y6[I3] = 3
y6[I4] = 4
y6[I5] = 5

print('ASCII WAVEFORM LABELS:', WLAB)
print('NUMERIC WAVEFORM LABELS:\n', y6)
print('CHECKING (positions should match with above):\n',subsetInfo['BinNo'])
```

```
ASCII WAVEFORM LABELS: ['NOISE_ONLY', 'P0N#1', 'P0N#2', 'Q3N#1', 'Q3N#2', 'Q3
N#3']
NUMERIC WAVEFORM LABELS:
 [0. 0. 5. 2. 0. 0. 0. 0. 0. 0. 0. 0. 3. 0. 3. 1. 0. 4. 0. 0. 5. 1. 0. 0.
 0. 0. 3. 0. 0. 4. 1. 0. 0. 0. 0. 2. 0. 2. 3. 1. 2. 0. 0. 0. 0. 0. 0. 0.
 1. 0. 2. 0. 0. 0. 0. 0. 0. 5. 5. 5. 0. 0. 0. 0. 0. 1. 5. 1. 3. 0. 0. 2.
 5. 0. 3. 2. 0. 2. 0. 2. 0. 0. 0. 3. 0. 3. 2. 0. 3. 0. 0. 2. 2. 2. 0. 0.
 0. 0. 5. 0. 0. 4. 5. 4. 1. 4. 1. 3. 2. 2. 0. 4. 0. 0. 1. 1. 0. 4. 5. 1.
 0. 0. 0. 0. 4. 3. 0. 0. 3. 0. 0. 1. 0. 0. 5. 0. 0. 2. 4. 1. 0. 2. 4. 4.
 0. 5. 0. 5. 0. 3. 3. 0. 2. 0. 0. 0. 0. 4. 0. 2. 1. 5. 5. 0. 5. 0. 1. 3.
 0. 0. 4. 0. 4. 4. 1. 0. 0. 5. 5. 2. 2. 0. 0. 4. 2. 0. 5. 0. 3. 0. 0. 0.
 4. 5. 1. 3. 4. 3. 0. 2.]
CHECKING (positions should match with above):
 0        NaN
1         NaN
2       Q3N#3
3       P0N#2
4         NaN
        ...
195     Q3N#1
196     Q3N#2
197     Q3N#1
198       NaN
199     P0N#2
Name: BinNo, Length: 200, dtype: object
```

In [15]:
```
#from sklearn.preprocessing import StandardScaler
from sklearn.linear_model  import LogisticRegression
from sklearn.model_selection import KFold

y = y6
X = MAT_S #The PCs

# Create a K-fold object
nfold = 5
kf    = KFold(n_splits=nfold, shuffle=True)
kf.get_n_splits(X)

# Number of PCs to try
ncomp_test = np.array([1,2,3,4,5,6,7,8,9,10,20,30,40,50,100,X.shape[1]])
#ncomp_test = np.arange(2,2  +1)
num_nc     = len(ncomp_test)
print("We will try %d # of PCs: "%num_nc, ncomp_test)
print('X.shape=', X.shape)

# Accuracy:  acc[icomp,ifold]  is test accuracy when
# using `ncomp = ncomp_test[icomp]` in fold `ifold`.
acc      = np.zeros((num_nc,nfold))
acc_comp = np.zeros((num_nc))

# Loop over number of components to test
for icomp, ncomp in enumerate(ncomp_test):
    print(":::------------------------------------------------")
    print(":::Trying (icomp,ncomp) = (", icomp, ',', ncomp, ')')
    # Look over the folds
    for ifold, I in enumerate(kf.split(X)):
        Itr, Its = I

        # Xtr, Xts, ytr, yts = ...
        Xtr = X[Itr, 0:ncomp]; ytr = y[Itr];
        Xts = X[Its, 0:ncomp]; yts = y[Its];

        # Use a logistic regression classifier
        logreg = LogisticRegression(multi_class='auto', solver='lbfgs', max_it
er=10000)
        logreg.fit(Xtr, ytr)

        yprob         = logreg.predict_proba(Xts)
        yprob_max     = np.amax(yprob,axis=1)
        yprob_max_ind = (yprob == yprob_max[:, None]).astype(int)
        yprob_1d      = np.zeros(yts.shape).astype(int)
        #There is probably a more direct way to do this
        for idx in range(1,yprob_max_ind.shape[1]):
          yprob_1d += (yprob_max_ind[:,idx]*idx).astype(int)
        acc_cf = (yts == yprob_1d).astype(int)
        #print('yts=',yts)
        #print('yprob_1d=',yprob_1d)
        #acc_cf = (yts == ypred).astype(int)
        acc[icomp, ifold] = np.mean(acc_cf)
        print("...kfold",ifold,"ncomp=",ncomp,"Accur=",acc[icomp,ifold])
    #end of inner for()
    acc_comp[icomp] = np.mean(acc[icomp,:])
```

```
    print("***Mean accuracy folding was",acc_comp[icomp],"(nc=",ncomp,")")
#end of outer for()
```

```
We will try 16 # of PCs:  [  1   2   3   4   5   6   7   8   9  10  20  30  4
0  50 100 150]
X.shape= (200, 150)
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 0 , 1 )
...kfold 0 ncomp= 1 Accur= 0.475
...kfold 1 ncomp= 1 Accur= 0.45
...kfold 2 ncomp= 1 Accur= 0.55
...kfold 3 ncomp= 1 Accur= 0.575
...kfold 4 ncomp= 1 Accur= 0.525
***Mean accuracy folding was 0.5149999999999999 (nc= 1 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 1 , 2 )
...kfold 0 ncomp= 2 Accur= 0.65
...kfold 1 ncomp= 2 Accur= 0.625
...kfold 2 ncomp= 2 Accur= 0.65
...kfold 3 ncomp= 2 Accur= 0.7
...kfold 4 ncomp= 2 Accur= 0.525
***Mean accuracy folding was 0.63 (nc= 2 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 2 , 3 )
...kfold 0 ncomp= 3 Accur= 0.85
...kfold 1 ncomp= 3 Accur= 0.575
...kfold 2 ncomp= 3 Accur= 0.575
...kfold 3 ncomp= 3 Accur= 0.625
...kfold 4 ncomp= 3 Accur= 0.75
***Mean accuracy folding was 0.675 (nc= 3 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 3 , 4 )
...kfold 0 ncomp= 4 Accur= 0.575
...kfold 1 ncomp= 4 Accur= 0.65
...kfold 2 ncomp= 4 Accur= 0.65
...kfold 3 ncomp= 4 Accur= 0.675
...kfold 4 ncomp= 4 Accur= 0.725
***Mean accuracy folding was 0.655 (nc= 4 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 4 , 5 )
...kfold 0 ncomp= 5 Accur= 0.675
...kfold 1 ncomp= 5 Accur= 0.725
...kfold 2 ncomp= 5 Accur= 0.625
...kfold 3 ncomp= 5 Accur= 0.75
...kfold 4 ncomp= 5 Accur= 0.675
***Mean accuracy folding was 0.6900000000000001 (nc= 5 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 5 , 6 )
...kfold 0 ncomp= 6 Accur= 0.6
...kfold 1 ncomp= 6 Accur= 0.575
...kfold 2 ncomp= 6 Accur= 0.7
...kfold 3 ncomp= 6 Accur= 0.825
...kfold 4 ncomp= 6 Accur= 0.675
***Mean accuracy folding was 0.675 (nc= 6 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 6 , 7 )
...kfold 0 ncomp= 7 Accur= 0.55
...kfold 1 ncomp= 7 Accur= 0.725
...kfold 2 ncomp= 7 Accur= 0.675
...kfold 3 ncomp= 7 Accur= 0.7
```

```
...kfold 4 ncomp= 7 Accur= 0.7
***Mean accuracy folding was 0.6699999999999999 (nc= 7 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 7 , 8 )
...kfold 0 ncomp= 8 Accur= 0.575
...kfold 1 ncomp= 8 Accur= 0.75
...kfold 2 ncomp= 8 Accur= 0.725
...kfold 3 ncomp= 8 Accur= 0.725
...kfold 4 ncomp= 8 Accur= 0.65
***Mean accuracy folding was 0.6849999999999999 (nc= 8 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 8 , 9 )
...kfold 0 ncomp= 9 Accur= 0.75
...kfold 1 ncomp= 9 Accur= 0.6
...kfold 2 ncomp= 9 Accur= 0.675
...kfold 3 ncomp= 9 Accur= 0.725
...kfold 4 ncomp= 9 Accur= 0.65
***Mean accuracy folding was 0.68 (nc= 9 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 9 , 10 )
...kfold 0 ncomp= 10 Accur= 0.725
...kfold 1 ncomp= 10 Accur= 0.725
...kfold 2 ncomp= 10 Accur= 0.625
...kfold 3 ncomp= 10 Accur= 0.8
...kfold 4 ncomp= 10 Accur= 0.475
***Mean accuracy folding was 0.67 (nc= 10 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 10 , 20 )
...kfold 0 ncomp= 20 Accur= 0.625
...kfold 1 ncomp= 20 Accur= 0.575
...kfold 2 ncomp= 20 Accur= 0.6
...kfold 3 ncomp= 20 Accur= 0.675
...kfold 4 ncomp= 20 Accur= 0.775
***Mean accuracy folding was 0.6499999999999999 (nc= 20 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 11 , 30 )
...kfold 0 ncomp= 30 Accur= 0.65
...kfold 1 ncomp= 30 Accur= 0.7
...kfold 2 ncomp= 30 Accur= 0.65
...kfold 3 ncomp= 30 Accur= 0.725
...kfold 4 ncomp= 30 Accur= 0.725
***Mean accuracy folding was 0.6900000000000001 (nc= 30 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 12 , 40 )
...kfold 0 ncomp= 40 Accur= 0.6
...kfold 1 ncomp= 40 Accur= 0.65
...kfold 2 ncomp= 40 Accur= 0.7
...kfold 3 ncomp= 40 Accur= 0.675
...kfold 4 ncomp= 40 Accur= 0.725
***Mean accuracy folding was 0.67 (nc= 40 )
:::-------------------------------------------------
:::Trying (icomp,ncomp) = ( 13 , 50 )
...kfold 0 ncomp= 50 Accur= 0.675
...kfold 1 ncomp= 50 Accur= 0.725
...kfold 2 ncomp= 50 Accur= 0.65
...kfold 3 ncomp= 50 Accur= 0.725
...kfold 4 ncomp= 50 Accur= 0.65
```

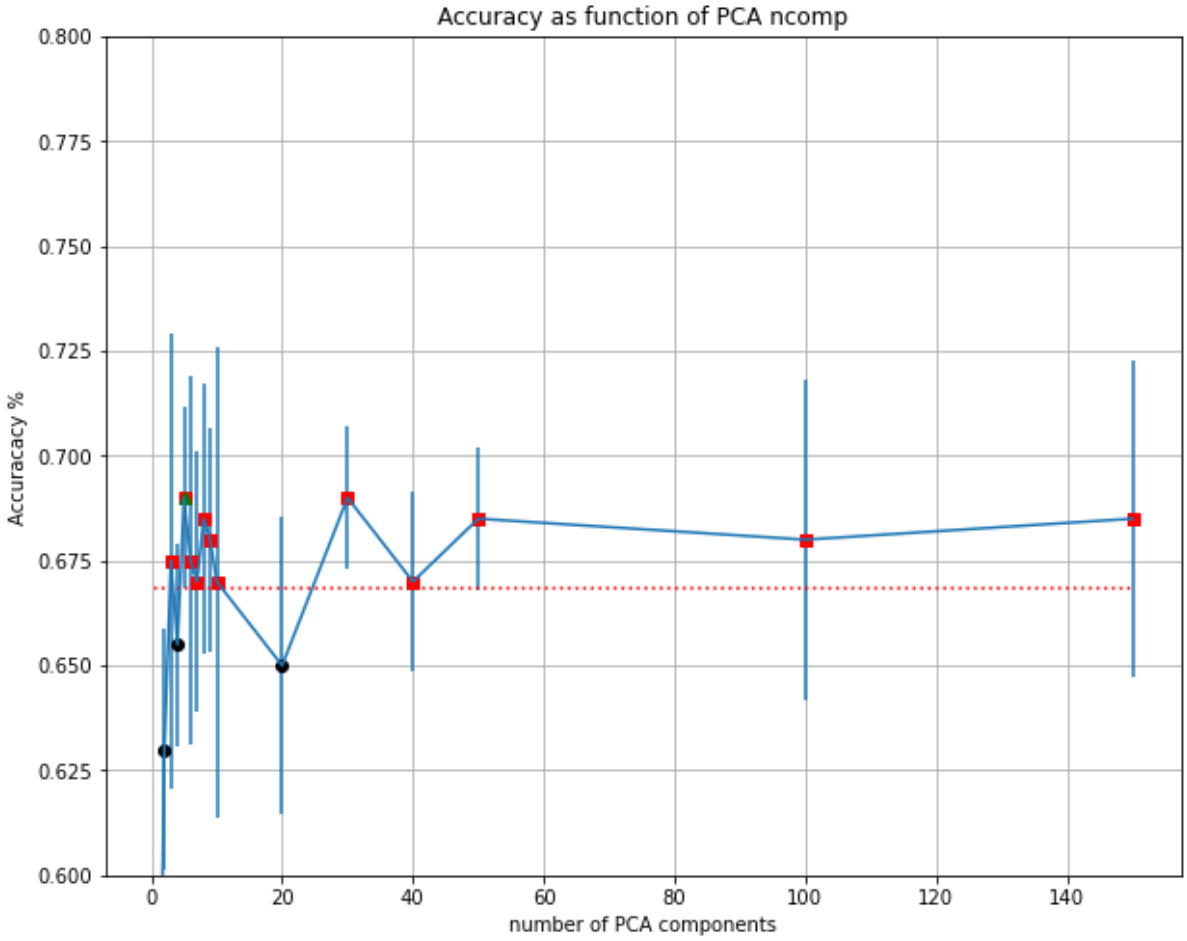
```
***Mean accuracy folding was 0.6849999999999999 (nc= 50 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 14 , 100 )
...kfold 0 ncomp= 100 Accur= 0.725
...kfold 1 ncomp= 100 Accur= 0.75
...kfold 2 ncomp= 100 Accur= 0.575
...kfold 3 ncomp= 100 Accur= 0.6
...kfold 4 ncomp= 100 Accur= 0.75
***Mean accuracy folding was 0.6799999999999999 (nc= 100 )
:::-----------------------------------------------
:::Trying (icomp,ncomp) = ( 15 , 150 )
...kfold 0 ncomp= 150 Accur= 0.725
...kfold 1 ncomp= 150 Accur= 0.7
...kfold 2 ncomp= 150 Accur= 0.55
...kfold 3 ncomp= 150 Accur= 0.675
...kfold 4 ncomp= 150 Accur= 0.775
***Mean accuracy folding was 0.6849999999999999 (nc= 150 )
```

AS we can see the results wer not great. However, some classification was still possible.

Below we should the optimal numbers of PCs for multi-class case according to the SE and NORMAL rules. Because now the standard errors are larger, the number of PCs vary more from run to run.

In [16]:
```
acc_mean = np.mean(acc, axis=1)
acc_se   = np.std(acc, axis=1) / np.sqrt(nfold-1)
plt.figure(figsize=(10,8))
plt.errorbar(ncomp_test, acc_mean, yerr=acc_se)

# Optimal order with the normal rule
# Optimal order with one SE rule
# Find the max R^2
imax    = np.argmax(acc_mean)
acc_tgt = acc_mean[imax] - acc_se[imax]

# Find the Lowest delay above the target
I = np.where(acc_mean >= acc_tgt)[0]
iopt = I[0]
dopt = ncomp_test[iopt]
print(imax, iopt, dopt, acc_tgt)
# Plot the line at the target level
plt.plot([acc_mean[0],ncomp_test[len(ncomp_test)-1]],[acc_tgt,acc_tgt],'r:')
plt.plot(ncomp_test, acc_mean, 'ko')
plt.plot(ncomp_test[I], acc_mean[I], 'rs')
plt.plot(ncomp_test[imax], acc_mean[imax], 'g^')
# Plot the line at the optimal model order
plt.plot([dopt,dopt], [0.9,1], 'g:')
plt.plot([ncomp_test[imax],ncomp_test[imax]], [0.9,1], 'k:')

plt.title('Accuracy as function of PCA ncomp')
plt.xlabel('number of PCA components')
plt.ylabel('Accuracacy %')
plt.ylim((0.6,0.8))
plt.grid()


# Print results
print("SE     RULE: estimated optimal order #pcs=%d"%dopt)
print("NORMAL RULE: estimated optimal order #pcs=%d"%ncomp_test[imax])
```

```
4 2 3 0.6682055052822967
SE     RULE: estimated optimal order #pcs=3
NORMAL RULE: estimated optimal order #pcs=5
```



Now we calculate the Confusion Matrix for the multi-class case.

Note that the results werew good only for detecting the presence and or not of the signal. There was significant mislabeling of the waveforms when they were present in the signal.

In [17]:
```
# ***TODO:  Print a confusion matrix
from sklearn.metrics import confusion_matrix

nn = X.shape[0]//2

Xtr = X[:nn, ]; ytr = y[:nn];
Xts = X[nn:, ]; yts = y[nn:];
logreg = LogisticRegression(multi_class='auto', solver='lbfgs', max_iter=10000
)
logreg.fit(Xtr, ytr)

yprob         = logreg.predict_proba(Xts)
yprob_max     = np.amax(yprob,axis=1)
yprob_max_ind = (yprob == yprob_max[:, None]).astype(int)
yprob_1d      = np.zeros(yts.shape).astype(int)
#There is probably a more direct way to do this
for idx in range(1,yprob_max_ind.shape[1]):
  yprob_1d += (yprob_max_ind[:,idx]*idx).astype(int)

C0 = confusion_matrix(yts,yprob_1d)
# Normalize the confusion matrix
Csum = np.sum(C0,axis=1)
C = C0 / Csum[:, None]
# Print the confusion matrix
print("\nConfusion Matrix - Normalized")
print(np.array_str(C, precision=3, suppress_small=True))
print("\nConfusion Matrix - Not Normalized")
print(np.array_str(C0, precision=3, suppress_small=True))
```

```
Confusion Matrix - Normalized
[[1.    0.    0.    0.    0.    0.   ]
 [0.273 0.182 0.273 0.091 0.    0.182]
 [0.    0.    0.9   0.1   0.    0.   ]
 [0.111 0.222 0.333 0.222 0.    0.111]
 [0.125 0.375 0.312 0.125 0.    0.062]
 [0.167 0.083 0.083 0.417 0.    0.25 ]]

Confusion Matrix - Not Normalized
[[42  0  0  0  0  0]
 [ 3  2  3  1  0  2]
 [ 0  0  9  1  0  0]
 [ 1  2  3  2  0  1]
 [ 2  6  5  2  0  1]
 [ 2  1  1  5  0  3]]
```

For Discussion (Future Work)

We can handle the spectrograms as images and train a Deep Netowrk to classify the signals. This may bring better results than PCA.

One idea is to use transfer learning and reuse a trained network like VGG16 to do the job, only training the final fully connected layer and perhaps the intiial convolution layers (because the images a bit different). This would be an interesting extension of this project.